UNIVERSITY OF ALBERTA

DYNAMIC BRAND CHOICE AND PRODUCT MARKET SIGNALLING UNDER IMPERFECT INFORMATION

BY

H. TÜLİN ERDEM ÖNCÜ

©

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The undersigned certify that they have read, and recommended to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled DYNAMIC BRAND CHOICE AND PRODUCT MARKET SIGNALLING UNDER IMPERFECT INFORMATION submitted by H. TÜLİN ERDEM ÖNCÜ in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY in MARKETING.

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March 26, 1993

To my mother and father, Tülay Erdem and Selçuk Erdem

ABSTRACT

The purpose of this dissertation research is to: (1) develop a framework showing the interdependencies in consumer risk and information search, brand choice and brand values and firm marketing mix decisions under imperfect information, (2) develop two structural models of brand choice, (3) test the proposed formal theory empirically.

I call a model "structural" if it is based explicitly on consumer utility maximization and its parameters are parameters of consumer utility functions and constraints. Both the structural models capture the impact of past consumption experience and advertising exposures on consumer uncertainty about brands and hence on consumer brand choice. The dynamic model, in which consumers maximize expected utility over the planning horizon, nests the static model, in which consumers maximize the immediate expected utility.

The models provide a behavioral explanation why current choices depend on past consumer histories and why future expectations may affect current choices. They shed light on the relations and differences among learning, brand loyalty, purchase feedback, advertising carryover effects, state dependence and unobserved heterogeneity. Furthermore, since the model parameters obtained from structural models are invariant to strategy changes, policy experiments based on these models provide unbiased results and hence they are useful in investigating the long-run implications of the marketing mix.

I estimate both the models from Nielsen scanner panel data on laundry detergent by employing simulation techniques (Keane and Wolpin 1992). Using the estimated structural models, I perform scenario evaluations to analyze how changes in marketing strategy affect brand choice in both the short-and long-run. Some of these policy experiments are only possible via the structural approach, and hence are new to the marketing literature.

The results indicate that the structural models are better able to explain "processes" than reduced form approaches and have better in-sample and out-of-sample fit.

The managerial implications of the proposed theory include: (1) A strong brand name may ensure the credibility of a firm's position, (2) Consistency in firms' signals (e.g. advertising) and the consistency of those signals with consumer experiences feed back into the long-run reputation associated with brand names.

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INTRODUCTION

Imperfect and asymmetric information affect the actions of buyers and sellers in the marketplace. Both the buying behavior of consumers and the marketing mix decisions of firms are sensitive to the informational structure of the market. In this context, both consumer brand choice behavior and the marketing mix decisions of firms also are affected by the informational aspects of the marketplace. For example, imperfect information about product characteristics and associated consumer uncertainty (informational aspects of the marketplace) has implications for consumer brand choice (Meyer and Sathi 1985, Roberts and Urban 1988). Indeed, the impact of uncertainty on brand choice may create temporal dependencies in consumer brand choice behavior and necessitate a dynamic analysis of consumer brand choice processes (Meyer and Kahn 1991).

Furthermore, uncertainty about product characteristics on the part of consumers influences the marketing mix decisions of firms. For example, advertising (Milgrom and Roberts 1986) and price (Gardner 1970) may be used as signals of quality about which consumers may be imperfectly informed. In turn, the marketing mix decisions of firms influence consumer brand choice.

Thus, consumer brand choices affect and are affected by a firm's "branding" and brand management decisions. In this sense, the value associated with brand names (Farquhar 1989, Shocker and Weitz 1988) is directly related to the informational aspects of a market and the marketing actions of firms (Erdem and Louviere 1992). In short, the impact of the informational structure on consumer brand choices and firm marketing mix

decisions and their interdependencies can be best understood and analyzed within a dynamic framework which takes both seller and buyer sides of the market into consideration.

Over the last decade a substantial literature on consumer brand choice has developed. Recently, attention has shifted to the dynamics of consumer choice behavior (Helsen and Schmittlein 1989, Jain and Vilcassim 1991, Papatla and Krishnamurthi 1992, Fader and Lattin 1992). Attempts to explain how consumers choose among brands in a product category over time also may overlap with efforts both to assess the long-run effects of the marketing mix (e.g., Carpenter and Lehmann 1985) and (within the context of panel or revealed preference data) to analyze market structure (e.g., Elrod 1988). Thus, one can try to understand purchase dynamics, assess long-run marketing mix effectiveness and analyze market structure within an integrative modelling approach that explicitly tries to account for factors that drive consumer behavior over time and make the process of brand choice endogenous.

Unfortunately, almost all published dynamic brand choice models of the last decade tried to capture the dynamics of brand choice by exogenously imposing a dependency between past and current choices (e.g., Jeuland 1978, Guadagni and Little 1983). One way to explain the dependence of current choices on past choices in a behavioral model is to introduce the informational aspects of the market in the models of brand choice (Eckstein, Horsky and Raban 1988). Specifically, imperfect information about product characteristics and hence consumer uncertainty can provide a behavioral explanation for this dependence (Meyer and Sathi 1985, Roberts and Urban 1988).

Thus, the purpose of this thesis is to: (1) develop a conceptual framework which captures the interdependencies among consumer risk and information search, brand choice, brand values and firm marketing mix decisions under imperfect information, (2) propose two formal structural models of brand choice under uncertainty about product characteristics by focusing on a subset of the conceptual framework, and (3) test the proposed models empirically, by estimating the models from scanner panel data.

I call a model "structural" if it is based explicitly on the consumers' maximization problem and its parameters are parameters of the consumers' utility functions or of their constraints. The two models I describe in this thesis are a static structural model which is a variate of the model proposed but not estimated by Roberts and Urban (1988) and a dynamic structural model. In these models, past consumption experience with a brand and past advertising exposures affect current choice because they reduce consumer uncertainty about product attributes, hence raising expected utility from a brand. The dynamic model, in which consumers make current choices to maximize long-run expected utility, nests the static model, in which consumers make current choices only to maximize current expected utility. The structural models discussed in this thesis enable me to analyze the relations and differences among purchase feedback, advertising carryover effects, brand loyalty, state dependence and unobserved heterogeneity among consumers. Thus, the models account for and explain different types of temporal dependencies in consumer choice.

Using the estimated models, I am able to perform a number of policy experiments (i.e., scenario evaluations) to find how changes in the marketing strategy affect brand

choice both in the short- and long-run. Some of these policy experiments are only possible via the integrative structural approach adopted in this thesis, and hence are new to the marketing literature. This is so because most existing brand choice models can be interpreted as reduced forms or approximations to reduced forms of the structural models studied in this thesis. In reduced forms of these structural models, the parameters capturing the dependence of current choice on past experience are functions of marketing strategy variables. This creates the potential for bias in the estimated outcomes of policy experiments based on reduced form models, since when using these models for policy experiments one assumes that the model parameters are invariant to policy. Structural models avoid this problem because parameters estimated from such models are invariant to policy (strategy) changes (Lucas 1976, Rust 1991).

To accomplish the previously mentioned purposes, this thesis is organized as follows: Chapter I reviews relevant literature. In Chapter II, I outline and discuss the conceptual framework. Then, I develop and present the formal models, outline the simulation results and discuss the models' implications in Chapter III. Next, I describe the method employed to test the proposed formal theory in Chapter IV. I outline the specifics associated with the data set used in the empirical analysis in Chapter V. Then, I present the estimation results in Chapter VI. Finally, I discuss the theoretical and methodological contributions of the thesis research, draw conclusions, and outline the future research agenda that follows from this thesis work in Chapter VII.

CHAPTER I

BACKGROUND

My study of dynamic brand choice and product market signalling draws upon several streams of literature. In this section, I first briefly discuss the marketing literature on dynamic brand choice under both certainty and uncertainty. Because uncertainty about "brands" and its impact on brand choice are closely related to both consumer information search and the generation of brand values (as I show in detail in Chapter II), I also review the relevant literature on information search, brand equity and the economics literature on brand values and product market signalling.

I.1. Choice Dynamics

I.1.1. Dynamic Choice under Certainty

Most probabilistic models of consumer choice behavior are static (McFadden 1974, 1981) assuming away temporal dependencies. However, violations of this assumption arise frequently: for example, tastes may change systematically as a consequence of learning, habit formation (Kuehn 1962, Jeuland 1978) or an explicit desire to seek variety in choice (McAlister and Pessemier 1982).

Several marketing research streams dealing with choice dynamics attempted to capture the impact of past behavior on current behavior. For example, Markov models for brand loyal (Morrison 1966), and variety seeking behavior (McAlister 1982) and linear learning models (Kuehn 1962, Aaker 1970) represent efforts to model choice as non-zero-order

Markov processes. The multinomial logit choice model also has been modified to capture dynamic choice behavior by introducing distributed lags of previous purchases into the indirect utility function (Guadagni and Little 1983). The linear learning model also has been extended to account for a first-order Markov process by Givon and Horsky (1978), who developed a heterogeneous linear learning model which was nested in a first-order Markov model. Finally, hazard models have been employed to capture brand switching behavior (Helsen and Schmittlein 1989, Jain and Vilcassim 1991).

Several brand choice models also incorporated the impact of marketing variables (especially price and promotion) on brand choice (Blattberg and Jeuland 1981, Guadagni and Little 1983, Keon 1980, Lilien 1974, Lehman and Carpenter 1985). For example, Zufryden (1980, 1981) adopted a two-brand Markov model of brand switching which related purchase explanatory-variables (e.g., product features, pricing, consumer characteristics, etc.) to switching probabilities.

Unfortunately, all these previously published brand choice models were approximations to "reduced form" models, and hence they cannot capture long-term effects of the marketing mix properly. The latter problem arises if one wants to evaluate the implications of a strategy change because the parameters estimated from approximations to "reduced form" models or from reduced form models change when the strategy changes. Thus, scenario evaluations based on the parameters estimated from such models render biased and incorrect results (Rust 1988). In contrast, "structural modelling" approaches[1] enable researchers to evaluate long-run effects of marketing mix decisions.

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[1]The structural modelling approach will be discussed in Chapter III and IV.

Not surprisingly, therefore, some attempts to capture advertising effects within the context of multinomial logit model (MNL) failed to find significant advertising effects (e.g., Tellis 1988).

Although different in form, Markov models, linear learning models and multinomial logit choice models that include "loyalty" variables share the common objective of parametrizing or measuring the degree to which brand choices made in one period affect choices in subsequent periods. For example, the linear learning model captures these effects as coefficients in the model. The Guadagni and Little (1983) model measures the importance of previous choices on the current choice as a coefficient of "loyalty" or "salience" (Meyer and Kahn 1990, p.109).

These streams of literature encounter conceptual and estimation problems in trying to deal with choice dynamics. The conceptual problems are primarily due to a failure to differentiate between "state dependence" and "unobserved heterogeneity" among buyers (McAlister and Srivastava, et. al. 1991, p. 242), whereas the estimation problems appear to be closely related to the lack of conceptual clarity about brand loyalty, state dependence and unobserved heterogeneity in the literature.

For example, Jacoby and Kyner (1973, p.1) assert that "there are at least 8 major operational definitions of brand loyalty". Prior to papers by Day (1969) and Jacoby (1971), brand loyalty was defined only in terms of outcomes (repeat purchase behavior), rather than reasons. More recently, an operational definition of brand loyalty as the exponentially smoothed sum of past brand purchases seems to have become well accepted (McAlister and Srivastava et. al. 1991). This definition of brand loyalty equates brand

loyalty to "state dependence"[2]. State dependence may occur because of the behavioral impact of the "past" on the "future" (true state dependence), or the impact of individual differences in unmeasured variables (unobserved heterogeneity) on choice (spurious state dependence). Thus, both unexplained heterogeneity among consumers and true state dependence create positive serial correlation among choices by the same individual, which makes it difficult to discriminate between the two effects. Thus, this approach to brand loyalty implies that if one controls for unobserved consumer heterogeneity, state dependence indicates brand loyal behavior.

On the other hand, a number of studies of choice dynamics attempted to capture unobserved heterogeneity by a "brand loyalty" variable calculated from past purchase data (e.g. Guadagni and Little 1983). Thus, brand loyalty often was equated to state dependence if unobserved heterogeneity was accounted for in the model; but unobserved heterogeneity was captured by a "brand loyalty" parameter in the same model, which appears contradictory.

To clarify these issues, there is a need to distinguish between brand purchases due to fit between individual tastes and brand attributes, and those dependent on past purchases (Wernerfelt 1991). Operationally, this corresponds to a distinction between the unconditional choice probability (i.e. not conditional on past purchase) and the conditional choice probability obtained by conditioning on past choice. Some segmentation efforts defined brand loyalty in terms of high unconditional choice probabilities (e.g., Grover and

---

[2]State dependence refers to the effect of past consumer choices on current behavior.

Srinivasan 1989), while others defined brand loyalty in terms of conditional probabilities. In the latter case, consumers exhibit brand loyal behavior if brand purchase increases the probability of purchase on the next occasion. This tendency has been referred to variously as "learning" (Kuehn 1962), "last purchase loyalty" (Morrison 1966), "inertia" (Jeuland 1979), "reinforcement" (Kahn, Kalwani, Morrison 1986) and "inertial brand loyalty due to time lags in awareness and cost-based brand loyalty due to switching-costs" (Wernerfelt 1991).

Indeed, the reasons underlying repeat purchase behavior should not be neglected in analyzing brand loyalty. Yet, because one cannot observe these "reasons" in data like scanner panel data does not necessarily imply that one cannot differentiate empirically among the various influences that underlie repeat purchase behavior. For example, true state dependence due to learning should not be defined as brand loyalty, nor should inertia be labelled as brand loyal behavior. Inertia is routinized behavior and could be the outcome of a low involvement process. Although inertia may lead to state dependence, it does not imply brand loyalty; indeed, inertia-induced repeat purchase behavior may be extremely sensitive to promotions (Assael 1987).

Strictly speaking, brand loyalty means "sticking with your brand", hence, state dependence due to learning, for example, cannot account for brand loyalty. It makes better behavioral sense to view brand loyalty as the result of a close fit between tastes and product offerings. Thus, heterogeneous consumer preferences partly explain why different consumers become brand loyal to different brands. In scanner panel data, these preferences are not observable and therefore accounting for unobserved preferences (one

type of unobserved heterogeneity) is an important issue because pooling consumers with heterogenous tastes without accounting for the taste differences results in biased parameter estimates (Heckman 1981). Indeed, Guadagni and Little (1983) used a "brand loyalty" variable (an exponentially weighted sum of past purchases) to accommodate heterogeneity among households. However, but they wanted also to capture the effects of past behavior on current behavior with the same measure. Unfortunately, the Guadagni and Little approach confounds the effects of heterogeneity and state dependence. Recently, a number of studies that ignored choice dynamics tried to capture unobserved preferences (to account for one type of unobserved heterogeneity) by assuming a parametric distribution over the brand-specific utility constants within a logit framework (e.g., Chintagunta, Jain and Vilcassim 1991)[3]. On the other hand, in a dynamic brand choice model, state dependence occurs if past behavior impacts current behavior. As noted earlier, Guadagni and Little's "brand loyalty" parameter tries to capture state dependence, but confounds state dependence with heterogeneity. Although there have been attempts to separate these two effects within the MNL framework (e.g. Fader and Lattin 1992), these involved statistical differentiation of those affects instead of accounting for them endogenously.

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[3]These models are called random coefficient logit models. Researchers often approximate the distribution of brand preferences (e.g. brand specific constants) by a discrete distribution with a finite number of support vectors and estimate the probability masses associated with these supports empirically from the data. For example, Jain, Vilcassim and Chintagunta (1992) allow for both unobserved heterogeneity in brand preferences (intercepts) and in the responses to marketing variables (slopes) with this approach. Other researchers captured unobserved preferences at the household or segment level by allowing each household or segment to have a different brand intercept (Higgens, Bass and Rao 1991, Russell, Bucklin and Srinivasan 1991).

Consequently they do not explain the process of choice dynamics.

In short, a major drawback of the dynamic brand choice literature is that the previous models were "approximation to reduced form" or "reduced form" models which tried to capture choice dynamics without solving for the choice probabilities endogenously. In contrast, to explain the formation of brand loyal behavior and its relation to state dependence and heterogeneity a "structural" modelling approach is needed. I propose two such structural models in Chapter III. The proposed models show that brand loyal behavior occur (given that preferences are matched with product offerings) if consumers' perceived risks associated with some brands are lower than perceived risks associated with other brands. The process by which consumers reduce perceived risk over time also changes utility over time (non-stationarity), which contributes to state dependence. How structural models disentangle these effects is discussed in Chapter III.

I.1.2. Models of Dynamic Choice under Uncertainty

The brand choice models discussed in Section I.1.1 assume that consumers have full information about brand attributes, but some authors have argued that full-information assumptions may be violated in many consumer buying situations (e.g., Ford and Smith 1987, Levin and Johnson 1985). Rather, uncertainty about product characteristics and associated impression-formation and learning effects may cause temporal dependencies in choice (Meyer and Kahn 1991).

Thus, uncertainty about attribute levels and risks associated with uncertainty may cause temporal interdependencies in choice behavior. For example, Meyer and Sathi

(1985) and Roberts and Urban (1988) treat the consumer as an expected utility maximizer, and model consumer brand choices under attribute uncertainty. As in static choice under certainty, these models assume that individuals choose that option which delivers the highest level of utility at the time of choice. However, the decision maker is uncertain as to what this value may be in a choice context the consumer maximizes expected utility. Thus, decision makers select the option with the highest expectation given a distribution of possible values. One further assumes that overall impressions (utilities) of choice options can be modeled as a multiattribute function of their attributes. In the uncertainty case, however, the attribute values are not known with certainty prior to choice, but rather are random variables (Meyer and Kahn 1991, p.110). For example, Roberts and Urban (1988) developed a mean-variance model of expected utility, modelling the updating of expectations as a Bayesian process. Instead of estimating their structural model, Roberts and Urban tested a subset of their model's implications. Specifically, Roberts and Urban investigated the impact of "word of mouth" and "test drives" on consumer risk in the context of new automobile purchases. Meyer and Sathi proposed that expected utility is a function of mean attribute levels, perceived dispersion around mean attribute levels and the interactions between means and dispersions. However, Meyer and Sathi do not explicitly incorporate underlying influences on the perceived dispersion around the mean attribute levels, hence a firm's actions are not integrated into their model.

Unfortunately, the dynamics of these models are limited to characterizing rational choice under uncertainty in the case where decision makers seek to maximize utility for the immediate choice occasion, and do not consider the impact of the immediate choice

on the stream of utilities gained from future choices (Horsky and Raban 1988). Eckstein, Horsky and Raban (1988) focused on sequential choice processes to capture the forward-looking nature of choice dynamics. Although they modelled the brand choice problem structurally and employed a dynamic programming approach, their model does not take a firm's actions into account. Their estimation method does not allow them to incorporate information sources other than the experience with a brand to model consumer expectations about brands.

Although not a brand choice model, Gatignon's (1985) investigation of the impact of advertising copy on consumer attitudes and purchase intentions is related to the literature on brand choice under attribute uncertainty. Like Roberts and Urban, Gatignon studied how consumers update brand expectations as they obtain new information by examining the impact of advertising and the variance of advertising-induced consumer perceptions on attitude and behavioral intentions. Thus, Gatignon ignored consumer learning within a dynamic choice framework, and focused on how advertising effectiveness influences behavioral intentions.

It is clear therefore that an important contribution to the literature on choice dynamics could be made by developing models which a) are not backward looking (Meyer and Kahn 1991), b) incorporate explanatory variables such as advertising, and c) capture the effects of consumer search on choice dynamics. The formal structural models of brand choice under uncertainty developed in Chapter III attempt to resolve these issues and fill a gap in the literature. Furthermore the method I propose to test the theory captures the nature of the underlying process as shown in Chapter IV.

I.2. Information Search

Consumer information search involves prepurchase information seeking. The focus of much previous research was on external information access in choice, and the dependent variable was usually the amount of search (Newman 1977, Midgley 1983, Carlson and Gieske 1983), rather than the resulting choice outcomes or preferences for alternatives. Alternatively, normative models of search often consider consumer search behavior within an expected cost and benefit framework based on theoretical work in information economics (Hey 1979, Stigler 1961). Shugan (1980) extended this framework to incorporate information processing costs. The cost-benefit approach is exemplified by the work of Furse, Punj and Stewart (1984) and Urbany (1986).

Meyer's (1981) descriptive model of search represents another view of search in which decision makers sample sequentially from a distribution of alternatives, each of which is characterized by a bundle of attributes. He models the process of information search under incomplete information about product attributes, and assumes that all information is obtained through overt examination. A key feature of his model is the way in which it assigns values to attributes before inspection, and updates them after search. This model separates utility into a riskless component, its dispersion, and the interaction between the two. This formulation also was used earlier by Pras and Summers (1978), and reappears in Meyer and Sathi (1985).

Of course, choice dynamics and information search are related, because when there is imperfect information about product attributes, there is uncertainty; hence, information

search becomes a way to reduce uncertainty and associated risks. Meyer and Sathi (1985) recognize this, but unfortunately treat search as a way to reduce uncertainty and formulate the process of search and updating of attribute levels in a regression framework[4] without explicitly formulating the antecedents of uncertainty in a truly dynamic framework. The formal model developed in Chapter III easily can be extended to incorporate search in a dynamic framework as shown in Appendix 1.

I.3. Brand Equity

Much recent work on brand names in marketing has dealt with the issue of brand equity (Farquhar 1989, Tauber 1988, Shocker and Weitz 1988). Recognition that brand names are assets to a firm that need to be valued led some researchers to investigate the sources and nature of this "added value that endows a product" (Farquhar 1989). This added value can be viewed from the perspective of the consumer or the firm (Shocker and Weitz 1988). Psychologically oriented research on consumer decision making suggests that brand names represent images, perceptions or beliefs based on past experiences and information (Jacoby et al. 1987), and these associations represent the means by which brands are positioned.

Thus, from a consumer's perspective, brand equity is the utility not explained by measured attributes (i.e. price, quality etc.) together with a clear, differentiated image that goes beyond simple product preference. Louviere and Johnson (1988) suggested that this

[4]Consumer updating of attribute levels after search (dependent variable) is linked to a number of explanatory variables.

"additional utility" can be measured by Brand-Anchored conjoint analysis, and Kamakura and Russell (1990) inferred it from actual consumer choices observed in scanner panel data.

From the firm's perspective, brand equity is defined as "the incremental cash flow resulting from a product with the brand name vs. the cash flow which would result without the brand name" (Shocker and Weitz 1988). Alternatively, one can define it to be as the capitalized expected future profits due to the association of a brand name with existing and potential products and services (Simon and Sullivan 1990). The impact of brand names on profits occurs via the firm's ability to engage in premium pricing, create brand loyalty etc. (Leuthesser 1988). Thus, previous literature has acknowledged the link between price and brand "equity" without explicitly explaining its nature and underpinnings.

One stream of brand equity research deals with brand extensions and transferability of brand equity, and seeks to understand how product associations are transferred from parent brands to extensions (Fry 1967, Aaker and Keller 1990). In this view, consumers are thought to transfer cognitive associations between parents and extensions according to the degree to which extensions match the attributes and benefits sought by consumers in the extended category. Thus, success or failure of brand extensions has been hypothesized to relate to the degree of complementarity in benefits offered, comparability in quality, communality of shared attributes, etc., between parent and extended product categories. Hence, such factors are assumed to underlie the "perceived fit" or similarity between parent and extended products (Aaker and Keller 1990, Tauber 1988,

Rangaswamy et al. 1989).

A review of this literature suggests that there is not yet a comprehensive framework with which the creation and transfer of the value associated with a brand name can be understood. For example, if brand equity is a function of brand name associations in consumers' minds, there must be some mechanism responsible for translating associations into "added values". One needs to explain this mechanism to understand, for example, what distinguishes brand value from brand image or why consistent positions are important to the management and transfer of brand values as suggested by previous research (e.g.,Shocker and Weitz 1988).

Thus, previous approaches to model and measure brand values do not explain the mechanism that underlies "additional utility" or "intangible" assets. The framework developed in Chapter II explains why brand names create "additional" utility and how they become an asset to the firm through a model that links firms' actions to consumer behavior under imperfect information and consumer uncertainty about product characteristics. The proposed framework links uncertainty and search in brand choice to a firm's marketing actions (including brand management) which sheds light on how the additional utility associated with brand names is created and why a "brand name represents a relationship between the customer and the firm" (Aaker 1991).

I.4. The Value Associated with Brand Names under Imperfect Information

The economics of information literature focuses on the informational aspects of the marketplace and discusses the role that brand names play when there is consumer

uncertainty about product characteristics. In one view, "quality" is the product characteristic about which consumers are imperfectly informed. This view distinguishes search, experience (Nelson 1970) and credence goods (Darby and Karni 1973)[5]. When there is informational asymmetry[6] (e.g., quality is known by producers, but imperfectly observed by consumers), reputation may serve as the mechanism that induces firms positioned as "high quality firms" to actually deliver high quality products. In this way, the loss of reputation associated with delivering less than was promised serves as a deterrent to cheating on customers.

For example, Klein and Leffler (1981) view brand names as private devices that serve to assure contract performance in the absence of a third party enforcer. Consumers recognize brand name capital investments (e.g. sunk selling costs like the use of expensive endorsers in advertising) made by the firm, and see them as an implicit warranty. Likewise, the firm's sunk costs induce it to offer the promised quality. Thus, consumers directly value brand name capital investments because these investments constitute an implicit guarantee. Klein and Leffler assume that consumers will cease to purchase brands that compromise on promised quality; hence the firm will suffer losses to both reputation and return on investments.

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[5]Search goods are goods whose qualities can be determined by the consumer by inspection prior to purchase. Experience goods are products whose qualities cannot be determined by the consumer without consuming them. Credence goods are products whose qualities of products which can not be fully known by the consumer even after trial.

[6]Asymmetric information exists if one side of the market has some information that the other side does not.

The implicit assumption of the Klein and Leffler model is that consumers can observe quality after consumption. The impact of a firm's cheating on repeat purchases will be weakened if consumers cannot perfectly judge quality after consumption, which may occur if a good has long-term experience characteristics or credence qualities (Darby and Karni 1973) and will be more severe if there also is inherent product variability (Roberts and Urban 1988) and/or product attributes change over time.

Reputation as a possible quality assurance also was investigated by Shapiro, who analyzed the choice of quality under both monopoly (1982) and perfect competition (1983). He modeled premiums for high quality products as returns to reputations under imperfect information. Telser (1980) suggested that a firm's investment in its brand name is analogous to posting a bond. A brand name serves to guarantee the quality of a firm's products, because the brand name is effectively forfeited if the firm reneges on this implicit guarantee due to the resulting damage to its reputation.

To summarize, the reputation literature[7] has concentrated on experience goods and on quality as the imperfectly observable attribute. Brand name investments (or the quality of a particular brand in previous periods in Shapiro's model) directly contribute to the reputation of a brand name (and a firm). Because consumers value this reputation, they are willing to pay higher prices for such brands, hence brand names have value. However, this does not necessarily mean that reputation leads to excess profits; and excess profits

[7]The reputation literature on brand names borrowed certain ideas from the literature linking advertising to goodwill (Nerlove and Arrow 1962). This comes as no surprise, given the interdependencies between brand names, advertising and other marketing mix variables as we see below.

may be dissipated not only by brand name investments but also by free entry (Allen 1984, Rogerson 1987). A related line of research considers the practice of using the same brand name for several products, and shows that a multiproduct firm can use its reputation as a bond for quality by using a brand name for an established product when it introduces a new experience good (Bhattacharya 1980, Wernerfelt 1988).

I.5. Price and Advertising as Signals for Quality

The issue of imperfect information about quality has been investigated by a number of researchers within a signalling framework. For example, there is a large body of literature in both marketing and economics on price as a quality signal (Akerlof 1987, Curry and Riesz 1988, Cooper and Ross 1988, Gardner 1970, Gerstner 1985, Stiglitz 1987).

Formal signalling models basically deal with the issue of signalling "existing quality" under imperfect information. Such models focus on price and advertising as signals for quality; and in some models, advertising and price are substitutable ways to signal quality (Kihlstrom and Riordan 1984, Milgrom and Roberts 1986). In this view advertising (or an introductory price offer) signals quality only if higher quality firms find it profitable to invest in relatively more advertising than lower quality firms, and conversely. This suggests that only high-quality firms can recover their excessive advertising costs because advertising high quality but offering low quality will not pay off. Thus, once again repeat purchases are an important mechanism to ensure that advertising functions as a signal. For example, Nelson (1974) suggested that it only pays high quality firms to advertise

heavily (as far as experience goods are concerned) because firms cannot recover their advertising costs if they cheat on their consumers. Unfortunately, this argument ignores the fact that low quality producers may have a cost advantage over high quality products. Thus, Tirole (1990) shows that whether advertising functions as a signal of quality depends on two conflicting effects: 1) the repeat purchase effect proposed by Nelson, and 2) the cost disadvantage effect of high quality sellers. For advertising to function as a signal, the latter effect[8] should be dominated by the Nelson effect.

In the marketing literature, Kirmani and Wright (1989) and Kirmani (1991) tested the impact of perceived advertising costs on brand evaluations and found that brand evaluations are related to perceived costs in an inverted-U fashion. Their results suggest that quality and brand perceptions rise with the level of perceived costs over an initial range of costs.

Theoretical work on product market signalling basically has been "partial-partial" equilibrium analysis. Hence, the consumer side of the market has been consistently neglected, and a model that focuses on the consumer side of the market derived from a more general framework is needed to fully understand how and why signalling works in product markets under imperfect information.

The next section proposes such a general dynamic framework drawing on the various streams of literature previously discussed. The conceptual framework links imperfect and asymmetric information and consumer uncertainty to product market signalling within a dynamic brand choice framework and the value of brand names.

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[8]The latter effect is called the Schmalensee effect (Schmalensee 1978).

CHAPTER II

BRAND CHOICE, BRAND NAMES AND MARKETING ACTIVITIES UNDER IMPERFECT INFORMATION: A SIGNALLING FRAMEWORK

Signals are defined as manipulable attributes or activities of economic agents which convey information to other economic agents in a marketplace (Spence 1974). Signalling is a way for an agent to communicate her type (i.e. characteristics) under imperfect information.

In most markets many differentiated products are offered, and consumers have imperfect information about the characteristics which differentiate these products. There is asymmetry of information between sellers and buyers: firms know more about the products they sell than consumers. Consumers' imperfect information about product characteristics may motivate firms to "signal" their product's location in attribute space. The first formal signalling model was developed by Spence (1974) to describe how job seekers can signal their ability to employers by investing in education. Education works as a signal because it should be related to ability if one assumes a negative correlation between the cost of education and ability (education is less costly to high ability individuals than low ability individuals). Furthermore, education itself may or may not increase the productivity of individuals; thus, in both cases education serves as a signal.

While the cost of signalling has been the focal point of models of job market signalling, returns to signalling have been emphasized in models of product market signalling as noted in the previous section. For example, some advertising models

(Kihlstrom and Riordan 84, Milgrom and Roberts 1988) assume that advertising costs are equal for all firms, and higher returns to advertising for high quality firms underlie advertising as a signal. Although the relative importance of returns to signalling in product markets is well-established, the costs of signalling should not be totally irrelevant. Even if the costs of advertising are the same across firms, the costs of having a credible brand name that serves as a signal (as shown below) may differ from firm to firm. For example, credible brand names can be maintained if signals are consistent. Not every firm has the same resources, technological skills or human capital to ensure the credibility of brand names. Hence, the costs of creating and maintaining credible brand names differ. Because costs associated with effective brand name signalling are inversely related to ability to create credible brand names, there may be a similar (although not identical) cost-ability relationship in product markets as that which operates in job markets.

II.1. The Conceptual Framework

Firms use their marketing mix elements to communicate with customers. Under imperfect and asymmetric information, certain marketing mix elements may become consumer information sources. Consumers face many differentiated products in a typical marketplace, and are imperfectly informed about various product characteristics. Not only is it costly to gather and process information about characteristics, but perfect information about brands may not be realized after consumption of a particular brand due to long-term experience or "credence" qualities, or changes in brand characteristics over time. Moreover, brand or product characteristics may not be the same across units of the same

brand or product at a given time (e.g. the characteristics of two cars of the same model in the same year may vary). Hence, perceived risk may exist even if a consumer has purchased a brand before. Thus, imperfect information and the associated uncertainty about product characteristics create a risk of getting a lemon[9] (in terms of vertically differentiated attributes like quality) or a "mismatched" product (in terms of horizontally differentiated attributes such as saltiness, i.e., consumers who like salt get less salty products). In this context, price becomes a product positioning tool as well as a signal. Advertising not only conveys direct information such as price or a new product launch information, but also conveys indirect information about a firm's capabilities (e.g. fly-by-night producers can not afford expensive endorsers). Hence, it serves as a signal.

Thus, marketing mix actions position products in attribute space, convey information and help consumers have clear images about them. In this view past and current marketing strategies make up the "brand name"; and brand names represent yet another tool to position products. However, brand names act like a "summary statistics" which differentiate them from other elements of the marketing mix. Brand names embody past positions, successes and failures of products with which they are associated. They represent the firm's sunk selling costs associated with the brand, and hence the history of the product.

History matters because brand names play a dual role as a signal: 1) They "summarize" where the brand is in attribute space somewhat akin to advertising, 2) they

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[9]Consumers may get lemons because firms may intentionally produce goods whose quality is less than promised. They also can get lemons due to inherent product variability which is unintentional, although controllable by the firm.

encapsulate the brand's past; and hence, may ensure the credibility of the firms' positioning under asymmetric information. This dual role explains the value associated with brand names. Brand names may represent an implicit contract and they signal[10] the "truthfulness" of a firm's positioning. They ensure credibility because firms that cheat on customers may lower their brand name values, which translates into reduced profits (e.g. some consumers may refuse to buy, or pay a price premium for the brand, etc.).

"Marketing activities" (i.e. market conduct box) are represented by broken lines in Figure 1.a, and briefly summarize a firm's marketing activities. Figure 1.a also shows the interaction between firms and consumers.

- Insert Figure 1.a about here -

Product positioning via brand names and/or other positioning activities provide an information flow to consumers. This flow embodies information about the product's location in attribute space and the credibility of that information as represented by consumer recognition of sunk selling costs. It helps consumers to better match their tastes with product offerings, and reduces their information gathering and processing costs (Shugan 1980) to achieve that match. At the same time, by informing consumers about the credibility of a position (i.e. the "credibility" of the information), brand names reduce consumer perceived risk.

Reduction of information costs and perceived risk translate into the "additional" utility

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[10]Given that various firms have brand name values, the relative magnitude of the values may signal to consumers the relative ability and/or willingness of the firms to deliver what they promise.

not explained by measured attributes (Louviere and Johnson 1988). In turn, increased expected utility increases brand choice probabilities because lower information costs and perceived risk should result in higher expected utility associated with a brand name and the probability of choosing that brand. It also should be the case that the links among imperfect information, risk, utility and choice exist even if the product or brand in question is only considered but not actually purchased.

Thus, brand values are associated with reductions in consumer risk and (possibly) information costs. Brand values exist as long as brand names function effectively as signals. For example, Ippolito (1990) differentiated between bonding and non-bonding signals of quality: the degree of bonding that a brand name offers determines its effectiveness as a signal.

Although several factors may influence the effectiveness of a signal[11], I consider only the availability of other devices to reduce consumer perceived risks and information costs. For example, product warranties or money-back guarantees may be thought as alternative mechanisms to reduce consumer risk. However, these devices are subject to adverse selection and moral hazard problems; hence, certain types of warranties may attract only certain types of consumers (e.g., comprehensive warranties may attract people who know they will be likely to need them), creating an adverse selection problem[12]. Moral hazard problems are especially important in product markets (Phlips 1988).

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[11]See Erdem and Louviere (1992) for a more detailed discussion of these factors.

[12]This is similar to the adverse selection problem in credit markets where high interest rates on loans may attract only high-risk people (Stiglitz and Weiss 1981).

Although the terms of warranties can be altered to reduce potential abuses on the buyer's side, it is difficult to eliminate them completely. On the other hand, brand names are free from moral hazard problems, which increases their effectiveness as signals.

Finally, one can consider the influence of "usage" on brand name values and brand choice. In frequently purchased product categories, the absolute amount of perceived risk may be lower than the perceived risk associated with infrequently purchased products. However, once a consumer chooses a brand whose expected utility is high because of low perceived risk but also has high visibility (Nedungadi 1990), the consumer may continue purchasing this product because of low involvement. The accumulated positive experience with such a brand may enhance brand values, enforce brand choice and foster brand loyal behavior.

For example, in the laundry detergent category Kamakura and Russell (1990) found a high amount of brand equity related to the order of brand entry in the market and the accumulated advertising investment. The proposed framework predicts these results by linking the accumulated advertising investments to the credibility of a brand name and accumulated positive experience with a brand to the enhancement of brand values.

The second dashed box in Fig 1.a shows how consumer responses to marketing decisions (i.e. brand choices) are translated into market performance measures such as profits, market share and loyalty. The third box with broken lines ties market structure into market conduct (marketing activities) and performance. Market performance measures (market shares, etc.), influence the structure of competition and the extent of entry barriers, and the opposite hold as well (i.e. the extent of competition influences market

shares). Furthermore, market structure (e.g., competition) influences marketing activities (e.g., pricing). Many of these relationships represent potential future research issues, and are not captured in my formal model, hence I do not discuss them in depth.

Thus far, we have seen how the actions of firms affect consumer behavior. Figure 1.b completes the picture by depicting how consumer information acquisition and perceived risks affect the actions of firms.

- Insert Figure 1.b about here -

A consumer who intends to buy a certain product engages in information acquisition, although an intention to buy is not necessary to accumulate information because most consumers are exposed to the promotional messages of firms frequently, and this accumulated "knowledge" can be used when the need or desire to buy the product arises. However, active search for information is generally initiated by an intention to buy because consumers are imperfectly informed about products, and it is possible that a product they bought under imperfect information might not match their wants or needs.

Thus, there is perceived risk on the part of consumers: and consequently, consumers are motivated to develop information acquisition strategies which force them to accrue information costs. Information costs include information-gathering and information-processing costs. Information-gathering costs include search costs borne by consumers, such as the monetary costs of accumulating information and time spent gathering it. Information-processing costs are the "costs of thinking" (Shugan 1980). These costs and potential risks are determined by many market, product and individual specific factors.

Product-specific factors include the extent of product differentiation in a particular

product class, average repeat purchase time of the product, degree of observability of product attributes before and after purchase and stability of the industry in question (whether product attributes and levels are stable over time). For example, a product which has not been changed often, which is frequently purchased, whose attributes can be evaluated easily probably does not require the consumer to consult expert opinions and/or *Consumer Reports*. Consequently, search costs and thinking costs will be fairly low (*ceteris paribus*) because the less information required, the less there is to process.

Individual-specific factors include the opportunity cost of time, income, level of involvement and education. The former three influence both the information acquisition strategy and total amount of information costs consumers will bear; while education may affect the potential costs of thinking. As depicted in Figure 1.b, information costs and perceived risk influence consumer expected utility which also appears in Figure 1.a. The major difference between the two figures, however, stems from the fact that Figure 1.b indicates that consumer information processing and risk affect the marketing mix. For example, if consumers obtain quality information from price, then firms price accordingly. If consumers are skeptical of advertising claims (i.e. doubt their credibility), then they will rely more on brand names than (the latest) advertising as an information source. This implies that brand management activities will gain in importance. Figure 1.b also shows that brand choice and associated experience with a brand provide brand-specific information to consumers.

Supply side considerations also may operate as effective constraints on marketing mix decisions. Furthermore, marketing mix activities also can motivate consumers to be in the

market or create a "need" for the product. These latter two issues are beyond the scope of the present research, but represent interesting potential future research questions.

The foregoing discussion of my proposed conceptual framework suggests that it differs from previous work in that it 1) explicitly integrates both seller and consumer sides of the market, 2) links values associated with brand names to other marketing mix decisions, 3) relates consumer search and brand choice to firms' actions, and 4) deals with product positioning in general, rather than only quality as an unobservable characteristic. Thus, the proposed conceptual framework also deals with non-quality related positioning issues.

CHAPTER III

A STRUCTURAL MODELLING APPROACH TO CONSUMER BRAND CHOICE

In this section the dynamics of consumer choice is modelled by considering the impact of attribute uncertainty on multiattribute preference formation. The formal models focus on only a small subset of the conceptual framework discussed in Chapter III: 1) the firm's activities are treated exogenously, 2) price does not provide any quality information, and 3) a game theoretic framework is not adopted, so the competitive actions-reactions of firms are not modelled.

In common with recent marketing and economics models previously discussed, the two structural models proposed have their roots in expected utility theory. Although some previous marketing models (e.g. Meyer and Sathi 1985, Roberts and Urban 1988) used expected utility theory to analyze the impact of uncertainty on immediate choices, my dynamic structural model considers a stream of utilities over time and integrates the impact of expected utilities associated with future choices on current choices.

Similar to Roberts and Urban (1988), attribute values are treated as a random draw from a normal distribution with a mean and variance, and consumers update their expectations based on new information using a Bayesian-like process. My model not only accounts for feedback from choice to expected utility, but consumers also consider the impact of current choices on their information sets, and hence on their future expected utilities. Therefore they may not choose brands that give the highest immediate utility as shown below. Thus, one of the models proposed in this chapter represents a "dynamic

structural" approach, which is hereafter termed 'the dynamic structural model' in the remainder of the thesis. The other model proposed in this chapter is nested in the dynamic structural model, and is hereafter called 'the static structural model'. It should be noted that both structural models capture the impact of the "past" (e.g. past purchases) on current choices; and hence, in this sense, both are dynamic. However, in economic structural modelling terminology, a model is "dynamic" only if "future" effects (e.g., future expected utilities affecting current choices) are captured. Hence, "the past effects only" model is the static structural model. The latter model is similar to the model proposed but not estimated by Roberts and Urban (1988). I elaborate on this issue below.

Structural models treat uncertainty and time explicitly. Decision makers are assumed to have well-defined objective functions and make decisions sequentially based on current information and beliefs about nature (the state space). The primitives of these models are the decision makers' preferences and their beliefs about nature, as well as the strategies of their opponents if there are any. Unlike structural approaches, reduced form approaches or approximations to reduced forms[13] do not attempt to derive behavioral implications from an explicit solution to an underlying decision problem. They ignore endogeneities in decision makers' behavior in that they do not account for the structure of the decision process. In structural models, not only is a theoretical framework specified, but often it also is estimated. Consequently, theory specification and testing are embedded. Given

[13]A reduced form specification implies that the structural model was specified and given the structural model, a reduced form is derived from the structural model. Logit models like the Guadagni and Little (1983) model are not even based on reduced form specifications. They are approximations to a decision rule/ reduced form.

parameter estimates, this allows researchers to simulate various scenarios and draw policy implications in a framework where all the restrictions imposed by the theory are satisfied. In the case of dynamic structural models, the estimation techniques involve applications of optimization theory to longitudinal data sets using dynamic programming[14] methods.

The structural models proposed below integrate not only attribute variability (also considered by Meyer and Sathi and Roberts and Urban), but also treat each experience (purchase) with a brand as a signal which provides imperfect information about product characteristics. Furthermore, the firm's signalling activity is captured by the firm's brand-specific advertising signals. The models also can be extended to capture changes in the mean levels of attributes, and incorporate consumers' search for information, as shown in Appendix 1.

III.1. Model Assumptions

The structural models are based on the following assumptions:

1. A brand's utility is assumed to be adequately approximated by an additive compensatory multiattribute utility model.

2. Consumers are not perfectly informed about mean attribute values, rather they are uncertain about them.

3. There is attribute variability, such that the attribute levels of individual units of the same brand may not be constant across units.

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[14]Dynamic programming is a method used for solving decision problems which can be broken down into a sequence of smaller decision problems.

4. Information obtained via advertising and/or experience about one brand provides no information about other brands in a market.

5. Experience with (use of) a brand provides information about product characteristics, but not necessarily perfect information.

6. In each period consumers may be exposed to one advertising message per brand which provides information about product characteristics.

7. Perceived variance and attribute weights are assumed to be uncorrelated. This assumption rules out range and similarity effects due to possible covariation between brand values and attribute weights (Curry and Menasco 1983).

8. Consumers are assumed not to choose more than one brand or buy more than one unit of that brand each period.

In addition to the above cited assumptions, the static structural model assumes the following:

9.a. Consumers are immediate expected utility maximizers. In each period, they choose the brand with the highest immediate utility.

The dynamic structural model has the following assumption in addition to the first eight assumptions:

9.b. Consumers maximize their expected utility over time, and consider the impact of their current choice on the stream of utilities to be gained from future choices.

Models that incorporate the impact of current choices on future utilities are sometimes called "multi-armed bandit" models in the dynamic programming literature (Whitle, 1982). In multi-armed bandit problems, different alternatives represent the arms of a gambling

machine. At each instant of time one can place a unit stake and try one of the arms. The different arms have differing (and unknown) probabilities of pay-offs, but as one acquires experience with an arm, one develops an estimate of its pay-off probability, which improves precision. The proposed dynamic structural model is similar to a multi-armed bandit process in which consumers have priors with respect to attribute levels of brands.

III.2. The Structural Modelling Approach

III.2.1. Consumer Expected Utility

Because attribute levels of different units of the same brand may not be constant, there is attribute variability. Roberts and Urban (1988) call this type of attribute variability "inherent product variability" (e.g. the quality level of individual products coming out of the factory may not be the same). However, this type of variability is at least partly under a firm's control, so I refer to it only as "attribute variability". Attribute variability may be expressed as:

$$A_{ijt} = A_{kj} + \xi_{ijt} \qquad \xi_{ijt} \sim N(0, \sigma^2_{\xi kj}) \qquad (1)$$

where A...refers to attributes which exhibit variability and which are not perfectly observable,

i...indexes consumers (i = 1,..,n),

k...indexes imperfectly observable attributes (k = 1,..,K),

j...indexes brands (j = 1,..,m),

t...indexes time (t = 1,..,T),

A_{kj}...refers to the mean attribute level of attribute k for brand j

Thus, equation 1 reflects the possibility that consumers can get "lemons". The error term associated with attribute variability is treated as an IID normal random variable, with zero mean and variance constant over time.

Purchasing and consuming a brand provides consumers with information, but consumers may not know exactly what they experienced[15]. This phenomenon is captured by equation 2[16]:

$$A_{Eijkt} = A_{ijkt} + \eta_{ijkt} \qquad \eta_{ijkt} \sim N(0, \sigma^2_{\eta kj}) \qquad (2)$$

A_E stands for the attribute level that a consumer believes s/he experienced, and η_{ijkt} refers to a random disturbance associated with consumer i's experience of brand j's kth attribute at time t. Thus, equation 2 captures the possibility that consumers may not perfectly evaluate what they received. Substituting equation 1 into equation 2, I derive an expression for information that a consumer obtains by purchasing and experiencing a brand with respect to the kth attribute:

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[15]There may be several reasons why consumer experiences may not provide perfect information: it may take a long time to learn about product characteristics (e.g., a consumer may discover that the detergent s/he uses takes the color off the laundry after several months of usage); the experience also may be context dependent (e.g., one stain may be tougher than another and a consumer may observe that a detergent does not consistently remove all stains).

[16]Equation 2 describes a psychophysical relationship. I am aware that the literature on psychophysics has shown that psychophysical relations are often non-linear. A linear relationship is posited only for computational ease; but does not alter the nature and/or analytical implications of the model in any major way.

$$A_{Eikjt} = A_{ikj} + \delta_{ikjt} \qquad \delta_{ikjt} \sim N(0, \sigma^2_{\delta ikj}) \qquad (3)$$

where

$$\delta_{ikjt} = \xi_{ikjt} + \eta_{ikjt}$$

and

$$\sigma^2_{\delta ikj} = \sigma^2_{\xi ikj} + \sigma^2_{\eta ikj} \qquad cov(\sigma_\xi \sigma_\eta) = 0 \qquad (4)$$

To summarize, consumer experience with a brand (i.e. the attributes of that brand) fluctuate around the mean brand attribute levels, and experience may provide only imperfect information. The two random components of the error term associated with fluctuations in consumer experience around mean attribute levels (η and ξ) cannot be separated empirically (unless a controlled experiment is designed). Therefore, they can be combined into a single term (δ), which refers to the variability of consumer experiences with the attribute levels of brands. This component also is IID normal.

The price that a consumer pays for a brand is net of price promotions. Consumers are assumed to know mean price levels, but not know when a brand will be on promotion.

$$P_{ijt} = P_{jt} + \omega_{ijt} \qquad \omega_{ijt} \sim N(0, \sigma^2_{\omega jt}) \qquad (5)$$

P_{ijt} is the price that consumer i pays for brand j at time t. P_{jt} is the mean price of brand j. ω_{ijt} stands for the price promotion revealed to the consumer at time t and which is IID normal. The i subscript captures the fact that different consumers go to different

stores and therefore face different prices.

A consumer's utility of consuming a brand is given by the following expression:

$$U_{ijt} = w_{ip} P_{ijt} + \sum_{k=1}^{K} w_{ik} A_{Eijkt} - \sum_{k=1}^{K} w_{ik} r A^2_{Eijkt} + e_{ijt} \qquad (6)$$

where U_{ijt}...is the utility for consumer i of brand j at time t

P_{ijt}....is the price consumer i pays for brand j at time t

w_{ip}....is consumer i's weight attached to price

w_{ik}.....is consumer i's weight attached to the kth (imperfectly observed) attribute

r.....is consumer risk coefficient

e_{ijt}.....is random component associated with consumer i, brand j and time t, assumed to be distributed as an IID Gumbel.

This specification suggests that utility is linear in the perfectly observable attribute (price), but quadratic in imperfectly observable attributes (A's). This implies that there are diminishing returns to these attribute levels. Consumption is assumed to occur in the range where marginal utility is positive. A strictly positive risk coefficient implies risk-averse behavior; hence, if consumers are risk-averse, uncertainty about attribute levels creates consumer risk (I estimate r as a free parameter). It also should be noted that utility is a function of experienced attribute levels and not the mean attribute levels (equation

6). The justification for this type of utility function can be found in Hanneman (1984)[17].

Given equation 6, the expected utility associated with brand j is:

$$E[U_{ijt}|I_{it}] = w_{it}P_{jt} + \sum_{k=1}^{K} w_{ik}E[A_{Eijkt}|I_{it}] - \sum_{k=1}^{K} w_{ik}r\,E[A_{Eijkt}|I_{it}]^2$$

$$-\sum_{k=1}^{K} w_{ik}r\,E[(A_{Eijkt} - E[A_{Eijkt}|I_{it}])^2] \qquad (7)$$

where E = the expectation operator and I = available information.

The expected utility of consuming brand j at time t for consumer i, given the information consumer i has at time t, is a linear function of price and a concave function of the expected levels of attributes which exhibit variability and the "variance" in these attributes. The expectation operator is omitted in the case of observed attributes because expected levels of perfectly observed attributes equal the actual levels of these attributes.

III.2.2. Consumer Expectations about Mean Attribute Levels

When a new brand is introduced, consumers' prior about the mean attribute level of the new brand (with respect to attribute k) is the product class mean (the time period that the new brand is introduced is taken to be 0 for notational convenience):

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[17]Equation 6 is an indirect utility function with the income term suppressed (the income terms cancel out later in the logit formulation). This specification is consistent with a family of direct utility functions which render corner solutions, which is a desirable characteristics because I assumed that consumers choose only one brand in each period.

$$E[A_{kj}|I_{i0}] = A_k \qquad (8)$$

From the consumers' perspective the mean level of the kth attribute of brand j is distributed normally with a mean equal to product class mean and an initial variance:

$$A_{kj} \sim N(A_k, \sigma^2_{vk0}) \qquad (9)$$

where A_k is the product class mean for attribute k and σ_{vk0} is the prior variance associated with attribute k (note that all consumers share the same prior variance).

Consumers have rational expectations about mean attribute levels, as expressed by equation 10:

$$E[A_{kjt}|I_{it}] = A_{kjt} + v_{ikjt} \qquad v_{ikjt} \sim N(0, \sigma^2_{vikjt}) \qquad (10)$$

Thus, consumers' expectation errors (v) are IID normal with zero mean and time-dependent variance. Substituting equation 3 and 10 into the variance component of equation 7 yields

$$E[(A_{Eikjt} - E[A_{Eikjt}|I_{it}])^2] \qquad (11)$$

and the perceived variance of attribute k:

$$\sigma^2_{Aikjt} = E[(A_{kj} - E[A_{kj}|I_{it}])^2] + \sigma^2_{\delta kj}$$

$$= \sigma^2_{vikjt} + \sigma^2_{\delta kj} \qquad (12)$$

Thus, the variance associated with an attribute is the sum of two variance terms: the variance associated with consumers' expectation errors of mean attribute levels and the variance associated with the consumer experience with that attribute. The overall perceived variance associated with a brand (i.e. perceived risk of a brand) is a weighted sum of perceived attribute variances:

$$\sigma^2_{(j)kt} = \sum_{k=1}^{K} w_{ikj}^2 \sigma^2_{kikjt} \qquad (13)$$

Thus, attribute uncertainty gives rise to perceived risk, which influences consumers' expected utility. Hence, the perceived risk associated with a brand is part of the additional utility created by a brand name as discussed in Chapter II.

III.2.3. Consumer Updating of Expectations

Consumers have expectations about both mean attribute levels and perceived risks associated with brands. They update their expectations each period after receiving new information. If a consumer purchases a brand in a given period, s/he receives information according to equation 3.

The firm's signalling constitutes another information source. I posit that consumers may receive one advertising message about any of the brands that advertise in each period. If S represents such messages, then each message signals about the attribute

levels[18] of a brand according to:

$$S_{kjt} = A_{jt} + \varsigma_{kjt} \qquad \varsigma_{kjt} \sim N(0, \sigma^2_{\varsigma kj}) \qquad (14)$$

The error term associated with advertising signals is assumed to be IID normal with zero mean and a variance which is constant over time.

Consumer expectations conditional on the information available are distributed as:

$$E[A_{kj} | I_{it}] \sim N(A_{kjt}, \sigma^2_{v\,ikjt}) \qquad (15)$$

Hence, one period ahead expectation of the mean attribute level (i.e. expectation of the attribute level at time t given the information available at time t-1) is given by:

$$E[A_{kj} | I_{i,t-1}] \sim N(A_{kjt}, \sigma^2_{v\,ikj,t-1}) \qquad (16)$$

For a given advertising signal, the expected level of the signal and the expected mean level of the attribute at time t, given the information available to a consumer at time t-1, are equal:

$$E[S_{kjt} | I_{i,t-1}] = E[A_{kj} | I_{i,t-1}] \qquad (17)$$

Similarly, the expected level of information obtained via experience and the expected

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[18]The term "advertising signal" is used here within the context of signal extraction: consumers try to use the information contained in the message taking the precision of the signal into consideration.

mean level of the attribute at time t, given the information available to a consumer at time t-1, are equal:

$$E[A_{E\mid ijt}\mid I_{i,t-1}] - E[A_{ijt}\mid I_{i,t-1}] \qquad (18)$$

A consumer updates her expectation of the attribute level using the information contained in the surprise element of the advertising signal she receives and information obtained via experience according to the following:

$$\begin{aligned} E[A_{ijt}\mid I_{it}] - E[A_{ijt}\mid I_{i,t-1}] \; + \; & D_{1ijt}\beta_{1jt}(A_{E\mid ijt} - E[A_{E\mid ijt}\mid I_{i,t-1}]) \\ & + D_{2ijt}\beta_{2jt}(S_{ijt} - E[S_{ijt}\mid I_{i,t-1}]) \end{aligned} \qquad (19)$$

where β coefficients capture weights consumers attach, respectively, to the surprise elements of the information obtained by advertising signal and experience. The variable D_1 equals one if a consumer purchases brand j (experience with brand j) at t, and is zero otherwise. D_2 takes the value of one if an advertising message about brand j is received at t, and is zero otherwise. β coefficients are calculated by regressing the expectation error of the attribute level on the surprise elements. The derivation results show that β coefficients are functions of perceived variance and experience (or advertising) variability. Thus,

$$\beta_{1jt} = \frac{\sigma^2_{vijt}}{\sigma^2_{vijt} + \sigma^2_{\delta jt}}$$

$$\beta_{2jt} = \frac{\sigma^2_{vijt}}{\sigma^2_{vijt} + \sigma^2_{\zeta jt}}$$

Then, an expression for the evolution of expectation errors about attribute levels over time (i.e. updating of expectations about attribute levels) and an updating formula for the perceived risk can be derived.

The expectation errors evolve over time according to the following process:

$$v_{ikjt} = v_{ikjs-1} + D_{1ijt}\beta_{1jt}(-v_{ikjs-1} + \delta_{kjt}) + D_{2ijt}\beta_{2jt}(-v_{ikjs-1} + \zeta_{kjt}) \quad (20)$$

The perceived variance (risk) associated with the level of an attribute is updated as follows:

$$\sigma^2_{vikjt} = \frac{1}{\frac{1}{\sigma^2_{vikjt-1}} + \frac{D_{1ijt}}{\sigma^2_{\delta kj}} + \frac{D_{2ijt}}{\sigma^2_{\zeta kj}}} \quad (21)$$

The perceived variance (risk) associated with the attribute k can be obtained by substituting equation 21 into equation 12. In turn, substituting the perceived variance of attribute k into equation 13 yields the overall perceived risk associated with brand j.

The updating formula given by equation 21 suggests that the perceived variance associated with a mean attribute level (and consequently the perceived variance of an attribute and the overall perceived variance of a brand) increases in last period's mean attribute level variance (history matters). Furthermore, perceived variance decreases in the signals received, such that the more precise the signals, the lower the variance. But, if

these signals are very noisy, then they will be ignored.

Signals sent by a firm (in my model, the advertising message) will be imprecise and noisy (i.e. high variance) when a firm's positioning is inconsistent. This inconsistency has two dimensions: 1) if a firm does not deliver what it promises in its advertising, the signal will be noisy, which will increase overall perceived variance, 2) inconsistency among a firm's messages (reliable car image vs. high status car image) also makes signals sent by firms noisy. The first dimension of inconsistency leads to an erosion of a firm's credibility; hence, successful brand management requires consistent positioning. The second erodes the firm's positioning (Ries and Trout 1986). I might also note that the model implies that confusion created by repositioning may be avoided by sending precise signals to consumers, which implies that advertising (or other signals that firms use) can play a powerful role in repositioning strategies.

Another implication of the model is that the less noisy the experience information, the lower the perceived variance. Holding constant perceptual "mistakes" that consumers make in evaluating brands, the lower the attribute variability (equation 1), the lower the perceived variance. Thus, standardization of quality (i.e., less variability in quality among different units of the same brand) should decrease consumer risk, a phenomenon which clearly can be seen to operate to the advantage of Japanese car producers in the U.S. market.

III.2.4. Consumer Dynamic Expected Utility Maximization

In each period consumers choose a brand. Let d be an indicator of the brand choice

decision, defined as follows:

$$d_{ijt} = \begin{cases} 1 \text{ if brand } j \text{ is chosen at } t \\ 0 \text{ if otherwise} \end{cases} \qquad \forall\, j \in (0,\ldots,m) = J$$

where J is the consumer's choice set, which is assumed to include all available brands.

In the static structural model, at each time period t a consumer chooses a brand that maximizes the expected utility at t. Thus, a consumer maximizes the immediate expected utility. This type of behavior yields choice probabilities of the standard logit form as shown below. On the other hand, in the dynamic structural model the choice process is more complicated because at each time period t a consumer chooses brand j that maximizes the expected present value of utility associated with the planning horizon (t=0,...,T). The formal solution to this problem is given in Appendix 3. I illustrate the nature of consumer dynamic brand choice here with a two-period example.

At time T, the value associated with the purchase of brand j is defined as:

$$V_{ij}(I_{iT}) = E[U_{ijT} | I_{iT}] \qquad (22)$$

which simply says that the value of choosing brand j at time T equals the expected utility derived from consumption of brand j at time T. The value function for person i at time T is defined as:

$$V_i(I_{iT}) = E \max_{j \in J} E[U_{ijT} | I_{iT}] \qquad (23)$$

Equation 23 indicates that the value to person i of having information I_{iT} is the expected maximum utility a consumer obtains at T given that s/he chooses a brand based on the information I_{iT}. Obviously, the more information a consumer has about various

brands, the higher the expected maximum utility s/he can achieve, and consequently the higher the value. At time T-1, the value associated with the purchase of brand j is

$$V_{i(j)}(I_{i,T-1}) = E[U_{ij,T-1}|I_{i,T-1}] + \gamma E[V_i(I_{iT})|d_{ijT-1}=1, I_{iT-1}] \quad (24)$$

where γ is a discount factor. Equation 24 indicates that the value of choosing brand j at time T-1 is equal not only to the immediate utility obtained from consuming the brand at time T-1, but also the additional expected value at time T of having the information I_{iT} that s/he will have at T if brand j is purchased at T-1. This illustrates the information gathering incentive of brand choice. A consumer may choose a brand j at time T-1 that has lower expected utility than another brand if the purchase of that brand leads to a greater increase in the value of information at time T. For example, consumers may wish to purchase a brand that they know little about rather than buying a familiar brand with higher immediate expected utility because they may discover that they like the unfamiliar brand better and future information is valuable.

Because consumers may not choose any brands at certain periods, the value associated with a no purchase option has to be specified. This value (payoff) is assumed to be a linear function of time. Thus, the value of no purchase at time t is assumed to be a constant plus the time coefficient multiplied by t. The value of brands that are not included in the analysis (lumped together in an "Other" brands option) is defined similarly. Thus, consumers may buy one of the brands under analysis, an "Other brand", or choose not to purchase in a give period. I elaborate on these issues in Chapter VI.

Initially, I specified the value (payoff) functions associated with the no purchase and

other brands to be a function of the amount of detergent bought in previous periods to account for inventory effects, but these effects turned out to be statistically insignificant, so was excluded from further analysis. Time trends are included in the analysis, because the payoff functions are expected to be increasing in time due to learning effects. I discuss this point further in Chapter VI.

It might be noted that in period T a consumer's choice problem is equivalent to a standard static choice problem; however, because consumers care about the information obtained from brand choices, the expected utility maximization at time T-1 is a dynamic choice problem. If γ is equal to zero, such that consumers ignore the future, the dynamic problem reduces to static brand choice. The extension of equation 21 to periods prior to T-1 is straightforward, and shown in Appendix 3.

III.2.5. Consumer Brand Choice Probabilities

In the dynamic structural model, a consumer's choice probabilities have a standard logit form at time T because T marks the end of the planning horizon. In the static structural model, a consumer's choice probabilities have the standard logit form at any time period t. Define E as the deterministic part of expected utility (that which does not depend on e_{ijt}). Then the probability that brand j is chosen at time T given the information set I_{iT} is (in both the models):

$$P_j(I_{iT}) = \int_{v,\,w} \frac{e^{E(U_{ijT}|I_{iT})}}{\sum_{j=1}^{m} e^{E(U_{ijT}|I_{iT})}} f(v)dv(v)\, f(w)dw \qquad (25)$$

Equation 25 is a standard logit choice probability conditional on the consumer's expectation (perception) errors (v) and utility weights (w). Because v and w are unobservable, the choice probability is an integral over the distribution of possible v and w values, which is a "heterogeneous logit" specification (McFadden 1991) with serially correlated errors. Assuming a parametric distribution over the w's allows brand preferences (unobserved heterogeneity due to unobserved preferences) and responses to the marketing mix to vary across households.

In the dynamic structural model, the probability that brand j is chosen at time T-1 given the information set I_{iT} is:

$$P_j(I_{i,T-1}) = \int_{v,w} \frac{e^{E(U_{ij,T-1}|I_{i,T-1}) + \gamma E(V_j(I_{iT})|d_{ij,T-1}=1, I_{i,T-1})}}{\sum_{j=1}^{m} e^{E(U_{ij',T-1}|I_{i,T-1}) + \gamma E(V_j(I_{iT})|d_{ij',T-1}=1, I_{i,T-1})}} f(v)dv(v)\, f(w)dw \qquad (26)$$

The probability that a brand is chosen at T-1 depends not only on the deterministic part of the expected utility obtained from consuming the brand at T-1 (as in the standard logit model), but also on how the purchase of the brand affects the information set available to the consumer at time T, which affects the time T expected utility. The choice probabilities derived from the dynamic expected utility maximization of consumers reduce probabilities obtained from a static structural model if the discount factor (γ) is zero. That is, if consumers are concerned only with the immediate choice occasion, and even if past purchase histories and marketing mix affect current choice, this can be captured by a static (structural) choice model. Hence, the static structural model (Equation 25) is a special case of the dynamic structural model (Equation 26) described earlier in this

section. Also note that the static structural model is similar to Roberts and Urban (1988) model[19]. Furthermore, if expected utilities in equation 25 are replaced by a linear equation of price, promotion and a brand loyalty variable, and if homogenous weights are assumed, one obtains the Guadagni and Little (1983) specification. Indeed, I estimated a version of the Guadagni and Little model with advertising to use as a benchmark model which I discuss in Chapter IV and VI. I should also note that the derivation of choice probabilities for periods prior to T-1 in the dynamic structural model is straightforward, as shown in Appendix 3.

III.3. ANALYTICAL IMPLICATIONS OF THE MODEL

The decision analytic framework (i.e. the expected utility maximization in my modelling approach) provides a *paramorphic* (Hoffman 1960) description of an individual's dynamic brand choice behavior, which is consistent with the perspective that consumers behave as if they follow some normative decision rule (e.g. Hauser and Urban 1977, 1979, Louviere 1988, Shocker and Srinivasan 1979, Urban and Roberts 1988).

The dynamic structural model proposed above suggests that consumers may sample different brands to learn about them. The intuition behind this type of behavior is quite simple and does not impose a great amount of cognitive effort on the part of consumers. Thus, although the decision process may be simple from the consumers' point

[19]Their model specification was not identical to the static version of the dynamic model proposed here. Furthermore, their model did not deal with repeat purchase and incorporated word of mouth instead of advertising. As mentioned before, they did not estimate the model, rather, derived some implications and tested them.

of view, sometimes simple processes can be captured only by complex models, while at other times, a complex process may be captured by a simple algebraic equation (Einhorn 1971).

The model also suggests that the brand sampling activity for learning has a greater impact on current choices when the product in question is purchased relatively frequently. In the extreme, if it is a once a life-time purchase, the value of information contained in each choice will not affect current choices. Furthermore, although this model applies straightforwardly to new product introductions and diffusion (given the product category choice), it can be applied to mature product markets as well. Thus, the model is consistent with Howard and Sheth (1969) conceptual framework, that is when consumers engage in repeat purchasing of products, they may sample brands to gather information (extended problem solving). Then the purchase decision process becomes routinized and consumers may buy a subset of brands repeatedly. However, the sampling activity for learning purposes may follow a cyclical pattern, i.e., consumers may sample brands at certain times due to new product introductions, attribute changes, etc.

The proposed models incorporate purchase feedback, cumulative advertising effects and consumer expectations about brands. Because they are structural models, researchers can use them to explain the formation of brand loyal behavior, the long run impact of advertising and promotion, etc. I return to these issues when discussing the simulation results in the next section.

Some straightforward analytical implications of the models can be expressed in the following propositions:

P1: Perceived risk will be lower; and, hence, choice probabilities will be higher

a: the lower the advertising variability (i.e. the variance of the advertising signal as specified in equation 14),

b: the more advertising signals that are received (*ceteris paribus*),

c: the lower the experience variability of consumers associated with a brand's attributes (i.e. the variance of A_E as specified in equation 3), and

d: the more experience a consumer has with a particular brand

These propositions follow directly from the updating formula of perceived risk (equation 21): regardless of whether the information is received via advertising or experience, the less noisy the information, the lower the perceived risk. In the case of advertising, consistency in product positioning is the key to less noisy signals, while for experience variability, less attribute variability (equation 1) gives rise to more consistent consumer brand experiences. Finally, unless the information received is very noisy, the more signals received, the lower the perceived risk.

P2: Brands with higher perceived risk (variance) will generate, *ceteris paribus*, lower choice probabilities.

Thus, keeping the risk unadjusted utility and the consumer's trials for information gathering purposes constant, riskier brands will have lower choice probabilities.

III.4. SIMULATION

I ran a series of simulations with the dynamic structural model to analyse the model's predictions with respect to consumer brand choice behavior. Chapter VII discusses

simulations (scenario evaluations) run with the parameter values estimated from empirical data using both of the structural models.

The parameters of the expected utility function are the utility weights (w_{ik}), the risk parameter (r), the initial perceived variance (σ^2_{vj0}); the expected brand attribute levels, which are functions of actual attribute levels (A_{kj}); and the perceived variance of attribute levels (σ^2_{Aikjt}) (Equation 12). In turn, the latter is a function of the advertising and experience variances (equation 21). I assumed the price coefficient to be -0.5, the attribute weight to be 6, the risk coefficient to be 0.10 and experience and advertising variability to be 0.5 and 3, respectively. The attribute levels are assumed to be 1, 2 and 3 (Brand 3 has the highest level of the latent attribute). Furthermore, I assumed price variability to be zero. Advertising frequency (a consumer's probability of seeing a commercial in a given week) is assumed to be 0.2. I fixed the mean price at $ 10.

Given values for the parameters, it is possible to solve the consumer's dynamic expected utility maximization problem[20] in the dynamic structural model. Also note that the assumed parameter values are very close to the parameter values estimated in the empirical analysis with real data.

By drawing experience and advertising signals and values of the extreme value error terms from a random number generator, choice outcomes can be simulated. This allows simulations to be conducted to see how choice probabilities respond to changes in brand attributes, experience variability, variance of advertising signals received and discount rates, etc. In this way, the simulation experiments can be used to study the behavior of

[20]I discuss how the dynamic programming problem is solved in Chapter IV.

consumers in the dynamic model, and offer marketing guidance about the effects of marketing actions such as changes in advertising frequency and accuracy on consumer choice. Furthermore, such simulations can shed light on the dynamics of the choice process captured by the model.

For simplicity in graphic illustration, I make the following assumptions in the simulation analysis which do not change the major implications of the model: 1) Tastes are homogenous, 2) There is one imperfectly observable attribute, 3) There are three firms producing three brands (e.g., three liquid laundry detergents), 4) Utility is increasing in the imperfectly observable attribute (e.g., it is increasing in cleansing power), 5) Brand 1 has the lowest level of the imperfectly observable attribute and brand 3 has the highest level of the same attribute, 6) In the baseline case, firms have identical marketing mix (price, advertising frequencies and variances, experience variance are the same across brands), 7) The planning horizon of the representative consumer starts at period 1 and ends at period 10, 8) Consumers know nothing about brands at the beginning of period 1. I should note that the payoff functions associated with the no purchase and other brands in these simulations are functions of time and number of past purchases (the latter included to capture inventory effects).

For 1000 representative consumers, I generated choice outcomes. The hypothetical scenario involves the introduction of three new brands (there are no existing brands and the product category choice is exogenous). The vertical axis of the graphs is the percentage of consumers buying a certain brand, and the horizontal axis is time. Solid lines represent the base case, broken lines capture the impact of various marketing

activities on consumer brand choice.

- Insert Figures 2 - 13 about here -

In the base case, under perfect information all consumers would buy brand 3 in all periods, because preferences are homogenous and brand 3 has the highest level of the desirable attribute. Under imperfect information, consumers learn about brands over time via advertising and experience. Thus, if a sufficiently large planning horizon is allowed and there are no changes in the market (e.g., no new brands etc.), imperfect information and information outcomes eventually converge.

The solid lines suggest that under imperfect information, given advertising exposure and experience histories, some consumers keep buying an "inferior" brand. Thus, the model accounts endogenously for a type of consumer heterogeneity that is different than that resulting from different taste weights. Different consumers have different "histories" which gives rise to different levels of perceived risk among consumers. There is state dependence because perceived variance is updated each period; hence, utility in one period affects utility in the next. In this context, brand loyalty is related to state dependence, because updating of perceived variance creates state dependence, and the lower perceived risk, the higher consumer utility. Different consumers have different brand "histories" (endogenous observed heterogeneity), brand perceptions (endogenous unobserved heterogeneity) and they may also have different preferences (preference heterogeneity) which I assume away. If there is no variety seeking[21], this explains why

[21]The model does not incorporate variety-seeking, however this type of behavior can be integrated easily. As I will discuss later, the product category I chose for the empirical analysis has been shown to be a low-variety seeking product category, hence this will

consumers may buy a subset of brands repeatedly. The model endogenously captures heterogeneity, state dependence, brand loyalty and their interactions endogenously. In contrast, reduced form models or approximations them, such as habit persistence models, assume that utility at time t is dependent at utility at time t-1 without explaining what underlies that dependency.

The major simulation results can be summarized as follows:

1) A temporary price cut (Figures 2-4) increases sales in the short run, but has no long run effects. This result is contingent on the fact that price is not a quality signal in the model. If price is a signal, consumer franchise may be hurt by frequent price cuts in the long run, which is a future research issue. Also note that reduced form static models predict a big change in sales following a price cut and can not forecast the long run effects.

2) When the advertising frequency of brand 1 is increased, there is an increase in sales only in the short run. Over time, consumers learn that this brand is not very good (Figure 5), and therefore increased advertising has no long run effects (The small spikes in other brands' sales are due to inventory effects which are incorporated in the simulation analysis). When brand 2 advertises more, there is a somewhat positive effect in the long run although the short run effect is still larger (Figure 6). When brand 3 increases advertising (Figure 7), sales increase in both the short and long run because advertising encourages trial; and if consumers become satisfied with the brand and learn after trials that it is superior than other brands (loyalty occurs), they keep buying it.

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not confound the empirical analysis.

3) Advertising variability (variance) seems to be important only in the case of the "superior" brand. Sales increase when variability is lower (Figures 8-10).

4) Increased experience variability has a negative impact on sales for both brand 2 and 3 (Figures 11-13).

III.5. MANAGERIAL IMPLICATIONS

The major implication of the proposed conceptual framework and the associated formal models are that both the formation of a marketing strategy and consumer brand choice are affected by the informational aspects of the marketplace.

Specifically in my models, brand names represent another marketing tool composed of and related to other marketing tools. They are an information source for consumers, and if current advertising messages and promotional activities lack source credibility, strong brand names may ensure the credibility of claims made by firms. Hence, the proposed framework suggests that advertising plays a more critical role in generating brand values than promotional activities. In turn, current claims and their consistency with consumer experiences feed back into the long run reputation associated with a particular brand name.

To be able to deliver the "promised" product to consumers, a firm should avoid both intentional and unintentional discrepancies between promised and actual product offerings. Quality standardization is an important way to avoid the latter, but delivering the promised product is only one aspect of consistent positioning. A second aspect is related to the consistency among various signals sent by a firm. Consistency in advertising

strategy even may relate to the consistent images created in advertising jingles. For example, the "Choosy mums choose Jif" jingle of Kraft, and its accompanying advertising copy provide a very consistent product image. In general, consistency among individual advertising signals sent by a firm enables consumers to better locate the product in attribute space, which reduces risk and information costs. This implies that high brand values are not necessarily associated with "top quality" products, because brand values also can arise from the value of information provided by brand names, which suggests that lower quality brands may create substantial values. For example, Chevrolet has consistently signalled to consumers that it represents a medium quality, reliable family car; hence, it may command a higher brand value than a higher quality car with less consistent positioning.

Thus, imperfect and asymmetric marketplace information suggests that marketing mix and brand management decisions should involve dynamic planning. The informational aspects of a typical market also suggest that important insights can be gained if consumer brand choice behavior is analyzed within a truly dynamic framework within which past behavior affects future utilities and expected future utilities affect current choices. In an uncertain marketplace, consumers are likely to be concerned with future as well as the immediate choice occasions.

Consumers' use of different information sources may provide managers with important segmentation insights. For example, some consumers may rely more heavily on brand name than search as an information source. Hence, identifying different segments based upon consumer risk reduction and information acquisition strategies has

implications for targeting and branding ("brand portfolio") strategies.

Based on this reasoning, two overall implications of the proposed framework for the "brand equity and brand values" literature can be summarized as follows:

1) Brand image, brand loyalty and brand equity are distinct, albeit related concepts. A clear brand image is part of a brand's value because clear images reduce risk and affect potential information costs. However, brand images exist in consumers' minds whether or not they consider a brand, or undertake search. Thus, even if a consumer does not consider buying a certain brand (or, indeed, any brand) in a certain product class, various signals about the product may cause her to form images of the product. Brand values, however, take into account the impact of the brand name on information costs and risk, but only exist if that brand or product category is in the consumer's consideration set. Hauser and Wernerfelt (1990) formally show that information costs associated with brands influence which ones are added to or deleted from consideration sets. Brand loyalty, on the other hand, is a consequence of brand name value; hence, brands with higher values often create higher and more stable repeat purchase rates than brands with low values. Brand loyalty cannot exist without prior purchase and use experience, whereas brand equity exists even if a consumer has never used a particular brand.

2) The proposed framework also sheds some light on the issue of transferability of brand values. For example, similarity or perceived fit and factors related to these concepts have been proposed to underlie transferability (e.g., Aaker and Keller 1990, Tauber 1988). The proposed framework suggests that a consistent position provides consumers with a clearer product image, which reduces risk and information costs. Perceived fit between

parent and extended product may induce a consumer to transfer the image of a parent product to an extension, and if the fit is perceived to be close, consumers may consider information conveyed by the parent's brand name to be relevant to judgements about the extension.

CHAPTER IV

EMPIRICAL TESTS OF THE THEORY I :

Solution and Estimation of the Structural Choice Models

As previously noted, one important feature of structural models is that the estimated parameters come from objective functions. A second important feature of these models is that the econometrics involved in estimating these models is closely related to the theory (Eckstein and Wolpin 1989). Hence, to test the theory underlying the structural models one has to solve the consumers' expected utility maximization described in III.2.4 and estimate parameters from empirical data. I solve the consumers' optimization problem using simulation techniques and estimate the parameters of the model from scanner panel data. In the case of the dynamic structural model, the consumer expected utility maximization problem is solved by the method of dynamic programming. As a benchmark model, I also estimate a variate of the Guadagni and Little model which can interpreted as an approximation to a decision rule/reduced form specification.

Although the formal models show how one can incorporate heterogeneity in tastes and in responses to marketing mix, I assume homogenous utility weights in the estimation procedure for reasons explained later. I also assumed the advertising and experience variabilities to be the same across brands in estimation to reduce the number of parameters to be estimated. I discuss the parameters of the models, differences among them and empirical results in Chapter VII.

In this Chapter I focus on the technical aspects of the estimation procedure used to

solve and estimate the dynamic model which involves solving a dynamic programming problem. To estimate the static structural model, the discount factor is set to zero, hence, there is no need to use the dynamic programming method. However, the estimation of both of the structural models share in common the simulation techniques used to calculate the expected attribute levels in each period (and to integrate out consumer expectation errors).

V.1. The Dynamic Programming Method (DP)

Dynamic programming (Bellman 1957) is a method applied to solve (and estimate) dynamic optimization problems (e.g., dynamic stochastic structural choice models). The major insight of DP is that the solution of a multiperiod problem can be reduced to a recursive solution of a sequence of two period problems. In the model proposed in Chapter III, the dependent variable (which is called a "control variable" in DP terminology) is the choice of brand, and the explanatory variables ("state variables") are the number of advertising signals received (exogenous) and the past purchase history (endogenous). The vector of state variables is called the state space. Given the information consumers have (as captured by the state space), consumers try to choose an optimal sequence of brands that maximize their utility over the planning horizon (t=1,..,T).

By the method of dynamic programming the problem for the last period T is solved first, given the state space at T-1. Having found the best choice (the choice of one alternative which may be to buy a certain brand or not purchase at all) for the last period contingent on the state space at time T-1, the two-period problem is solved by choosing

an optimal alternative (choice), contingent on the state space at T-2. Having found the optimal choices for T and T-1, the three period problem is similarly solved by choosing the optimal alternative at time T-2, and so on. In the last stage, the optimal choice for the first period is found, given the information available at the beginning of period 1 (state space at t=1). Thus, the problem is solved backward in time step by step, a problem in T unknowns (T choices over t=1,...,T) is transformed into T problems. Also note that with stochastic disturbances (extreme value error terms in the utility function and normal errors in the signals received), the proposed model is a stochastic model (rather than deterministic), therefore optimal choice at t can be determined only after the state space at t-1 is observed.

IV.2. Estimation Procedure I: The Basics

Given the information on the state space available in the scanner panel data set, static and dynamic structural model parameters are estimated using the method of maximum likelihood (ML). Estimation of stochastic structural discrete choice models entails two steps: First, the consumer optimization problem must be solved numerically for a given set of parameters (in the case of the dynamic structural model, the dynamic optimization problem is solved by the DP method via backwards recursion described in the above paragraph). The parameters of the model are the utility weights (w_{ik}), risk parameter (r), initial perceived variance (σ^2_{vi0}), brand attributes (A_{kj}), advertising variance ($\sigma^2_{\zeta kj}$) and experience variance ($\sigma^2_{\delta kj}$). Then, given these parameter values, it is possible to construct the likelihood function for the observed choice data. The solution to the consumer

optimization problem is embedded in an iterative estimation procedure to obtain maximum likelihood estimates of the parameters.

To estimate the model, I use nested numerical solution algorithms. A nested numerical solution algorithm consists of an "outer" nonlinear optimization algorithm that generates the likelihood function for the parameter vector θ, and an "inner" algorithm that solves the optimization problem for each trial value of θ. The likelihood function for both the structural models is given by:

$$Log\text{-}L(\theta) = \sum_{i=1}^{n} \sum_{t=0}^{T} d_{ijt} \ln P_j(I_{it}, \theta) \qquad (27)$$

The form of these choice probabilities was given in equations 25 and 26. This log-likelihood function can be maximized using a standard "outer" optimization algorithm like BHHH (Amemiya 1985).

The embedded estimation procedure is an extremely computationally burdensome process, because the solution of the optimization problem involves high order integrals over the distributions of the unobservable stochastic processes that drive decisions (i.e., the error terms associated with experience and advertising signals and expectation errors). For example, consumers' expectation errors (ν_{ikjt}) are not observed, so must also be integrated out to form the choice probabilities. Since the (ν_{ikjt}) follow a complicated dynamic process (equation 20), this integration is non-trivial. Furthermore, it is necessary to evaluate these integrals at each point in the state space. In addition, given a solution to the optimization problem, the discrete choice probabilities needed to construct the likelihood function again are high order integrals over the same random variables.

Recently, there has been intense research in econometrics into simulation estimation of models (McFadden 1989, Pakes and Pollard 1989). In the simulation approach, one uses Monte-Carlo methods to simulate the high order integrals that enter the likelihood function rather than evaluating them numerically (Pakes 1987, Keane 1991). Unfortunately, these simulation methods only can be used to estimate static models.

Very recently, Keane and Wolpin (1992) proposed a new approximation method to solve discrete choice dynamic programming problems based on simulation and interpolation. It requires one to simulate the expected maxima of the value functions only at a subset of the state points. Then, the simulated expected maxima are used to fit an interpolating regression that provides fitted values for the expected maxima at any other point for which values are needed in the backwards recursion solution process described in IV.1.1. Keane and Wolpin's method allows one to circumvent Bellman's "curse of dimensionality" and obtain approximate solutions for problems with extremely large or even infinite state spaces.

Keane and Wolpin performed a number of Monte-Carlo experiments on this approximate solution method and concluded that it performs quite well on several dimensions: 1) it produces optimal decision paths very similar to those produced by the true solution, 2) estimation based on this approximation method embedded in a simulated maximum likelihood procedure produces parameter estimates with negligible bias from a substantive (behavioral and economic) point of view, and 3) the estimates do very well in out-of-sample prediction, and produce simulated policy effects very similar in most cases to those predicted by the true parameter values in conjunction with the exact

solution method.

Some quasi-reduced form approaches to solution and estimation of dynamic structural models also have been developed as well (Hotz and Miller 1989, Manski 1988). These methods use alternative representations of the future component of the choice-specific valuations that do not depend explicitly on the structural parameters of the model, but are estimated from data on future choice. The inherent limitation of these approaches is that they cannot incorporate the existence of individual specific unobservables as a component of the state space, generally ruling out serial correlation patterns in processes that drive decisions (e.g., expectation errors in the proposed models).

Therefore, I used the Keane and Wolpin approximation technique to solve and estimate the proposed structural models. In the case of the dynamic structural model, I approximate the expected maxima by Monte Carlo integration. Thus, to solve the expected maxima for T at time T-1, I first drew randomly selected states at T-1 before the brand choice decision. Then, at a given state space point, I took 100 draws from the joint distribution of all "random" variables (i.e. advertising signals, dummies for whether a consumer is exposed to an advertising or not-, experience signals, prices[22] and expectation errors). Next, I calculated the maximum of the value functions over the choice set for a given draw and averaged over the 100 draws to obtain the estimated expected maximum. I repeated this procedure for 100 randomly selected state points, and then regressed the calculated 100 expected maxima on the randomly selected 100 state points as summarized by the perceived variance and expected attribute levels at that state.

[22]Price has a normally distributed random variable component (See Equation 5).

Parameter estimates from this "interpolating regression" constitute the solution to the DP problem. Thus, the "future" component of the value function is calculated by using the parameter estimates obtained from the interpolating regression. In effect, one estimates an interpolating "regression" for each time period starting with time T (backwards recursion).

The calculated expected maxima enter the choice probabilities (equations 25 and 26) which, in turn, enter the likelihood function. Given the expected maxima, parameters of the model are estimated via maximum likelihood estimation. Then, given the estimated parameters, the DP problem is solved again with the new parameter estimates. The procedure iterates until a maximum is reached (i.e., the log-likelihood value stops improving significantly).

It again should be noted that the process of expectations formation and updating (i.e., the impact of "past" on current choice) is common to both the static and dynamic structural models. Consequently, the integration over this process to form the likelihood function must be done by simulation in both models. Thus, the estimation of the static structural model involves Monte Carlo simulations to get the updated levels of expected attribute levels in each period. The static structural model was estimated in the same way as the dynamic structural model, but the discount factor was set to zero in the case of the static structural model.

IV.3. Estimation Procedure II: Specifics

IV.3.1. The Initial Conditions Problem

Consumer choices are not observed starting from t=0, but only after some initial time t_1. Consequently, one does not actually observe consumer's information sets before t_1. This is a classic initial conditions problem. The initial conditions problem could be solved if the analyst knew the probability that a person is in each of the possible states at t_1 (where the analyst's observations start). This allows the likelihood function to be modified by replacing unconditional choice probabilities with choice probabilities conditional on the states at t_1 times the probabilities of those states. In the case of the dynamic structural model, the probability of every possible state at time t_1 can be obtained by solving the dynamic program all the way back to t=0. The modified log-likelihood function has the form:

$$Log\text{-}L(\theta) = -\sum_{i=1}^{n}\sum_{t=t_1}^{T}\sum_{I_{it_1}} d_{ijt}\ln P_j(I_{it}[I_{it_1}],\theta)\ P(I_{it_1}|\theta) \qquad (28)$$

where $I_{it}[.]$ is the implied information set at time t given consumer experiences from t_1 to t and given that they had information set I_{it} at t_1. $P(I_{it} \mid \theta)$ is the probability, given the parameter vector θ, that consumer choices from t=0 to t_1 generate the information set I_{it}. These probabilities are calculated when the dynamic programming problem is solved back to t=0. A computational problem arises if t_1 is large because the number of possible information sets at t_1 is large, and forming the summation over possible information sets at t_1 becomes computationally burdensome. Hence, as a practical matter, I solved the

2initial conditions problem by using the first two years of the data set to compute the state space (information set of consumers) at t_1, and imputed the state space at the beginning of the calibration period by using the first two years of past purchase histories. There were no advertising data available for this period, hence mean advertising exposure levels (probability of being exposed to an ad per week times number of weeks) were used to impute past advertising histories before the start of the calibration period. Once the state space at t_1 was imputed, the initial variance could be estimated and I could draw expected attribute levels from a normal distribution. It is worth noting that the expected attribute levels drawn at the beginning of the calibration period are not conditional on consumer (household) purchase histories, although in reality they are conditional on histories. Therefore using the first years of the data to solve the initial conditions problem is only an approximate solution.

IV.3.2. Estimation of the Attribute Levels

I estimate the mean attribute levels of brands (A_{kj}) as parameters of the model. These levels are not observed in scanner panel data. Thus, the estimation procedure of these attribute levels is linked to the "internal" market structure analysis. "Internal" market structure analysis tries to infer brand positions (i.e. attribute levels) and brand preferences (attribute weights) from revealed preference data such as scanner panel data. The methods employed to estimate market maps (analyze "the market structure") using data such as scanner panel data might be also termed as *revealed preference* mapping approaches (Elrod and Winer 91).

Elrod and Keane (1992) developed factor-analytic specifications useful for market structure analysis. The factor-analytic specifications impose a factor structure on the covariance matrix of the deterministic part of consumer-specific utility over households. Elrod and Keane estimated a probit model using a "common and specific factors" specification (i.e. mean brand preferences are assumed to be explained in terms of the common factors of the covariance matrix). Indeed, Choice Map (Elrod 1988) can be thought as a "common factors only" specification within a factor-analytic framework. I also estimate the actual attribute levels in the model; (A_{kj}) as "common factors"[23]. Thus, also the formal model I propose positions brands in a product market map like in other mapping approaches. However, unlike most previous models my structural models take into consideration variability in consumer utilities over time.

IV.3.3. Unobserved Heterogeneity

Unobserved preferences (w_k) and responses to the marketing mix (w_p) can be captured by a "heterogenous logit" formulation of the choice probabilities as shown in Chapter III, which is how one type of "unobserved heterogeneity" is captured. However, I do not estimate a model with heterogenous weights, rather I assume homogenous weights in the estimation procedure. Homogenous weights are assumed for two reasons: 1) I incorporate "unobserved heterogeneity" endogenously by allowing consumers to have

[23]See Elrod and Keane (1992) for further discussion and elaboration of these issues.

different perception errors and hence different perceptions about brands[24]. Indeed, the structural models show that "within household variation over time" and "variation between households" are correlated, because consumers become "heterogenous" over time due to different perception errors and different purchase and advertising exposure histories. 2) I have to solve the DP problem for each w_i to estimate the dynamic structural model with heterogenous preferences and marketing mix responses, which makes the estimation procedure computationally even more difficult[25]. Hence, this issue is left to future research.

I might also note that assuming parametric distributions of utility weights may be considered a "theoretical drawback", although it has been popular in marketing in recent years. For example, Rust argues that assuming parametric distributions over intercepts and/or slopes is basically "admitting ignorance" (Rust 1991) because the way unobserved heterogeneity is captured in these cases is atheoretical and at most a statistical procedure. At one extreme, one may let all the parameters of a model vary over individuals and obtain a perfect fit without explaining any "behavior".

IV.4. Empirical Tests of Theory: An Overview

Chapter VI reports and discusses the estimation results. The adequacy of the estimated models are assessed with standard goodness of fit measures. I also compare the two

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[24]The theoretical discussion of the model incorporated the "heterogenous weights" case to describe the model within the context of the previous models of brand choice.

[25]Note that even to estimate the static structural model with homogenous weights 357 integrations (number of alternatives x number of periods) have to be performed.

structural models and test whether the dynamic model is statistically different from the static structural model. Furthermore, I also estimate a Guadagni and Little (GL) like model with advertising effects (i.e., a multinomial logit model with lagged purchases). I introduce advertising effects into the GL model by means of an "advertising variable" (similar to the "brand loyalty" variable that roughly corresponds to experience effects) which is computed as an exponentially weighted average of past advertising exposures. I detail the estimation when I discuss estimation results in Chapter VI.

I also assess the out-of-sample fit as a very strict test of predictive validity (as opposed to in-sample goodness of fit). Thus, I predict the choices of different sample of households using parameters estimated from the calibration data set.

Given the estimated model, propositions 1.a through 1.c can be tested, respectively, by simulating the impact on brand choices of a change in advertising variability, number of advertising signals received and experience variability (scenario evaluations). The impact of the experience associated with a brand on perceived variance (and consequently on choice) can be assessed given the parameter estimates of experience variability and initial variance. Since advertising and experience variability are not observed in these data, parameters for these effects must be estimated to fit the data. These variabilities generate a very special serial correlation pattern (see equation 20); which enabled me to identify their parameters. Proposition 2 is supported if I cannot reject the hypothesis that the risk parameter (r) is negative (risk averse behavior).

Before discussing the estimation results (Chapter VI), I first discuss specifics associated with the data set used in the empirical analysis in Chapter V.

CHAPTER V

DATA

The data used to estimate and test the models developed in this thesis are scanner panel data for laundry detergent provided by A.C. Nielsen, Inc. The data set includes over 3000 households, from two test markets in Sioux Falls SD and Springfield MO. Daily data is available for a three year period from 1986 through 1988. A wide variety of variables is available for both cities, including prices, promotions, in-store displays, number and value of coupons used, etc. Sixty percent of the panel of households had a telemeter connected to their television set for the last 51 weeks in the data set, hence commercial viewing data are available for that period.

I used scanner panel data for two reasons. 1) the brand choice models I proposed and my analysis of advertising and experience effects on brand choice are closely related to the accumulated scanner panel research in marketing, and 2) an experiment would have added another stage to the empirical analysis. Indeed, I eventually expect to use experimental data, analyzing them in the same way as scanner panel data. Thus, using scanner panel data is logical first step within a bigger research programma I outline in Chapter VII.

V.1. The Product Category

I chose laundry detergent as the product category to model for the following reasons:

a) Detergents are relatively frequently and regularly purchased products. My empirical

tests require relatively frequently purchased product categories to capture the impact of future utilities on current choices. This is not to say, however, that the proposed model cannot be applied to infrequently purchased items like durables; rather, it is merely to note that for categories like durables, the impact of future "purchases" and their associated utilities should be negligible, which should result either in statistically insignificant discount factors (γ) or low values associated with future expected maxima.

b) New brands were introduced during the time under investigation; thus, there is an incentive for learning.

c) Previous research has shown detergents to be low in variety seeking (Elrod 1988). The model I propose currently does not capture variety seeking so, it is desirable to use a product category where variety seeking is not much of an issue.

d) Kamakura and Russell (1990) showed that there is a substantial amount of "additional utility" associated with brand names in this category. If a product category is chosen where there is no additional utility created, one may conclude (*inter alia*) that uncertainty is not an important issue in that category.

e) Firms heavily advertise in this category.

Although the data set contains information on both liquid and powdered detergent purchases. I investigated liquid detergents, because

a) In model estimation, I restrict the number of unobservable attributes (or imperfectly observable attributes from the consumers' point of view) to one to keep the number of parameters to be estimated to a manageable number. Previous market maps of laundry detergent data revealed that there are two dimensions in the attribute space: cleansing

power (or something similar to that) and whether the product is liquid or powdered (Elrod and Winer 1991).

b) I want to control as much as possible for multi-purpose purchases of detergent (e.g., consumers may buy both liquid and powdered detergents, but for different uses), because that type of behavior may be captured incorrectly as brand switching due to price (promotions etc.) or learning.

c) I choose liquids because there were three new liquid brand introductions as opposed to one new powdered brand introduction during 1986-88.

V.2. The Data Set

I use the Sioux Falls data as the calibration sample mainly because these data render a bigger sample than the Springfield data and there are fewer TV viewing gaps in the commercial exposure data for Sioux Falls. In this market, the two market leaders were Wisk (Lever) and Tide (P&G). During 1986-88, Dash, Surf and Cheer were introduced. The market shares during this period are given in Table 1.

Table 1
Market Shares in 1986-88

Brand	Market Share
Wisk	19.32 %
Tide	18.51 %
Era	12.30 %
Surf	10.96 %
Solo	5.75 %
Cheers	5.63 %
Dash	2.74 %

There are four brands with market shares of less than 5 %. I included them along with some smaller brands and generics in an "Other" category. Brands listed in Table 1 are the seven brands I analyzed. Dash was included despite a below 5 % share because it was one of the three newly introduced brands. Its market share is relatively low because it was introduced last.

The last 51 weeks of the 1986-88 period is used as the calibration sample period because commercial exposure data are only available during that period. I used the data from the fist two years to solve the initial conditions problem.

The Springfield test market is used to assess out-of-sample fit, although Dash and Solo are not available in this market. I also might note that use of liquid detergents is much lower in Springfield than Sioux Falls.

V.3. Panel Member Selection Criteria

The households included in the calibration (and the hold-out) sample fulfil the following criteria:

a) They must have had a telemeter attached to their TV.

b) 80 % of their total detergent purchases must had been liquid detergent purchases.

c) They must have had at least 20 liquid purchases over 1986-88.

d) In the last 51 weeks (calibration sample period), they must have had at least 7 and at most 24[27] liquid purchases. The number of purchases required in (c) and (d) gives me

[27]There were a few outliers with very large number of purchases.

a sufficiently large sequence of purchases for analysis and ensures relative homogeneity in purchase frequencies.

167 households fulfilled the above criteria in Sioux Falls and are the calibration sample. 48 households passed the above criteria in Springfield and are the validation sample.

V.4. Description of Variables Included in the Analysis

The control variable (dependent variable) is brand choice. Consumers could choose among the seven brands previously listed, an "Other" brand, or they may not purchase. I use weekly data. A household's purchase or non-purchase in every week is recorded as its choice in that given week. I ignored multiple purchases of the same brand in a given week. The screening tests I conducted revealed that multiple purchases of the same brand or different brands in a given week is a rare event.

The two "exogenous" variables in the structural models are price and advertising exposure. The price variable (P_{ijt}) is the marked price at a specific store. The price data utilize data from the purchase history file (consumer purchases over time) and the retail tracking file (store sales). The "mean" price (P_{jt}) is calculated as follows: I found the average price per 64 oz for each day, and I averaged these prices over weeks. If there were days during the week with no sales, I used in the average price for the week. If the whole week had no sales, I used the average price for the whole sample period adjusted for inflation. It is important to note that I calculated the average price over non-promotion days.

I did not include the coupons in the analysis. One problem associated with data on coupons is that one does not observe the availability of all brands' coupons. Thus, using the "after-coupon" price as the price measure may bias price coefficient estimates and exaggerate the impact of coupons. Additionally and more importantly, coupon usage is endogenous; hence, the price paid by a consumer is the price marked at a store plus a dummy to indicate whether brand j was bought or not times the coupon value. Such a brand dummy creates a very serious endogeneity problem. Hence, I tried to replace " the brand dummy times the coupon value" by a coupon availability proxy (calculated from data), which is exogenous, and subtracted that from the marked price. However, the goodness of fit of all the models was worse when measures for coupon usage were introduced than when they were not; and the parameter estimates in all models also were more sensible when coupons were excluded. Hence, I excluded coupons from the analysis.

It should be noted that excluding coupon availability measures from the analysis may result in attributing certain brand switches to learning when the real reason might have been coupon availability. However, the reverse argument holds as well. If no reliable data exist for coupon availability for all brands under consideration, one may attribute a switch to a coupon although the switch might have been caused by another factor (e.g. learning). Not only the goodness-of-fit of the structural models but also the goodness-of-fit of the GL model were worse when the coupon measures were included; hence, I concluded that using the coupon availability measures biases the results more than not using them.

I calculated the price variability (i.e., the variance of the prices: see equation 5) of the brands from data. Mean prices and price variabilities in Sioux Falls (calibration

sample) are shown in Table 2 (Price variabilities are reported as standard deviations):

Table 2
Mean Prices and Standard Deviations
(Sioux Falls)

Brand	Mean Price	Standard Dev.
Dash	2.86	0.25
Cheer	3.71	0.31
Solo	3.92	0.37
Surf	3.49	0.42
Era	3.86	0.41
Wisk	3.26	0.35
Tide	3.71	0.36

Table 3 reports the mean prices and price standard deviations for Springfield:

Table 3
Mean Prices and Standard Deviations
(Springfield)

Brand	Mean Price	Standard Dev.
Cheer	4.01	0.31
Surf	3.46	0.39
Era	4.09	0.41
Wisk	3.65	0.38
Tide	4.13	0.28

Advertising exposure data were compiled from the commercial viewing files. If a household's TV was tuned to a channel on which a commercial was aired during the full duration of the commercial, I assumed that the household was exposed to the commercial.

If the household was exposed to a commercial at least once during the week, I assumed it received an advertising message during that given week.

The advertising frequencies[27] associated with different brands in both cities are reported in Table 4:

Table 4
Advertising Frequencies

Brand	Sioux Falls	Springfield
Dash	0.10	----
Cheer	0.17	0.27
Solo	0.00	----
Surf	0.23	0.13
Era	0.57	0.81
Wisk	0.74	0.17
Tide	0.51	0.11

Using the parameter estimates obtained from the model, I ran several policy (strategy) experiments (simulations) which include also scenarios where advertising frequencies and mean prices are altered. I discuss these in the next Chapter.

[27]The advertising frequency associated with a brand is calculated from the commercial viewing files. Using these files, I created a series of dummy variables. If a household was exposed to a commercial at least once in a given week, that household had an advertising dummy of 1. Advertising frequencies were obtained by dividing the sum of these dummies by the total number of households over the 51 week period. Thus, the advertising frequencies can be interpreted as the "consumers' probability of seeing an ad in a given week".

CHAPTER VI

EMPIRICAL TESTS OF THE THEORY II :

Data Analysis

I estimate three models: 1) an approximation to a reduced form model, that is a multinomial logit model with lagged variables (past purchases and advertising exposures) which I call the Guadagni and Little (1983) model (GL), 2) a static structural model and 3) a dynamic structural model described in Chapter III.

The GL model I estimate is a variate of the original GL model. In particular, I did not estimate a size loyalty effect and my price variable includes promotions, hence, I do not have two separate price coefficients, and I introduced an "advertising" variable. The advertising variable in the GL model is an exponentially weighted average of past advertising exposures. As in the case of the original GL model, the "brand loyalty" variable also is an exponentially weighted average of past purchases, which corresponds to "experience" effects in the structural models. I estimated the smoothing parameters of the "brand loyalty" and "advertising stock" variables as parameters of the model. GL assumed the brand loyalty smoothing parameter to have an initial value of 0.75 and estimated it iteratively, whereas subsequent research usually assumed that this parameter had a certain value[29]. In contrast, I estimated the model by the standard method of maximum likelihood.

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[29]See Fader, Lattin and Little (1992) for a detailed literature review.

As previously noted (Chapter III), the static structural model is nested in the dynamic structural model. I first estimated the discount factor parameter in the dynamic model, as a parameter, which turned out to equal 1.001, and was statistically significant. However, the standard error, of was 0.02, was high from a theoretical point of view because a standard error of 0.02 for the weekly discount factor implies that the annual discount rate may fall in a wide range. Hence, I set it to the value of 0.995^{30}, which is a conventional assumption in applied dynamic programming research. Indeed, it is often very difficult to get an estimate of γ, and in many cases researchers have been unable to obtain an estimate (possibly because of their poor specification of the theoretical model). The intertemporal factor is usually assumed to be between 0 and 1 because it is assumed to be 1/(1+interest rate) although behaviorally that does not have to hold.

In all three models, the value of "Other" brands at time t is specified as:

$$V_{Ot} = \phi_O + \psi_O \, t \qquad (29)$$

Similarly, the value of no-purchase at time t is:

$$V_{NPt} = \phi_{NP} + \psi_{NP} \, t \qquad (30)$$

I specified and estimated alternative forms of these equations (e.g. I included household size as a variable), but the above specifications produced the best fit. As I discuss in Chapter VII, future research will attempt to integrate the inventory behavior

[30]Whether the value of γ is 0.995 or 1.001 does not change the estimation results.

into the structural models, which will enable me to derive equations 29 and 30 structurally from the model.

Parameter estimates and in-sample and out-of-sample goodness of fit tests are discussed in the next section.

VI.1. Parameter Estimates

VI.1.1. GL Model

The parameters of the GL model are the price coefficient (w_p); the "brand loyalty" coefficient (w_E), which can be interpreted as the "Experience" coefficient; the "advertising "coefficient (w_{Ad}), which can be conceptualized as capturing the impact of advertising on consumer brand choice; the brand intercepts (a); no-purchase (NP) and other brands (O) constants (Φ) and slope coefficients (ψ) (Equations 29 and 30); and the brand loyalty and advertising smoothing constants[31] (α_E and α_{Ad}, respectively). The parameter estimates and t-statistics are reported in Table 5.

The price coefficient is negative and statistically significant, whereas the brand loyalty coefficient is positive and statistically significant. Thus, "past purchases" associated with a brand (or "Brand Loyalty" as GL defined it) increases the probability of brand choice. All the brand intercepts and smoothing constants are positive and significant. The intercept of the first brand (Dash) is fixed at 0 for identification reasons.

The most important result in Table 5 is that, although the advertising coefficient has

[31]Guadagni and Little called the smoothing constant of the brand loyalty variable the "carry over constant" and denoted it as α.

the right sign (i.e. positive), it is not statistically significant. Thus, the estimated GL model suggests that advertising does not affect brand choice.

Table 5
GL Model Estimates

Parameter	Estimate	t-statistic
w_p	-1.077	-18.10
w_E	3.363	53.18
w_{Ad}	0.144	0.31
a_{Dash}	0.000	.....
a_{Cheer}	1.115	8.87
a_{Solo}	0.917	7.22
a_{Surf}	1.382	14.43
a_{Era}	1.601	11.03
a_{Wisk}	1.102	6.78
a_{Tide}	1.700	12.29
Φ_O	-0.633	-2.98
ψ_O	0.011	4.87
Φ_{NP}	1.636	8.02
ψ_{NP}	0.005	1.35
α_E	0.770	50.62
α_{AD}	0.788	2.95

-LL = 7463.23 AIC = 7478.23 BIC = 7531.10

The parameters of the payoff functions associated with "Other brands" and "No Purchase" indicate that the payoff associated with "Other brands" increases over time (ψ_O is positive and statistically significant). The constant terms in these functions turned out to be significantly negative in the case of "Other brands" and significantly positive in the case of "No Purchase". One might say that the utility associated with "Other brands" is

less than the utility derived from brands under consideration, but, I do not want to overinterpret the GL results. The payoff functions are estimated so that the GL results can be compared to the results of the structural models. Approximations to reduced form models like the GL model do not impose much, "theory", therefore it is not possible to interpret all the parameter estimates behaviorally. A good example of this is the meaning of the brand loyalty concept in GL. Table 5 indicates that the "past purchases" captured by the brand loyalty variable affect brand choice (the coefficient of the brand loyalty variable is positive and statistically significant). However, the GL model does not shed any light on "how" and in which context this happens.

VI.1.2. The Structural Models

The static and dynamic structural models have the same set of parameters which are the price coefficient (w_p); the weight attached to the (imperfectly observable) attribute k (w_k); the risk coefficient (r); the initial variance (σ_{v0}) (estimated as standard deviation); the "actual" or "mean" attribute levels of the brands (factor loadings) (A)[31]; the no-purchase (NP) and other brands (O) constants (Φ) and slope coefficients (ψ) (Equations 29 and 30): and experience and advertising variabilities in standard deviation form (σ_δ and σ_ς, respectively). I estimated one "latent" attribute (A) for each brand. For identification reasons, the attribute level of one brand had to be fixed. I fixed the attribute level of Tide (brand 7) to be 0.138 in the static structural model, 0.124 in the dynamic

[31]A's are imperfectly observable from the consumers' point of view. They are "latent" variables to the analyst.

model with T=51 and 0.120 in the dynamic model with T=100[32].

I estimated the dynamic structural model with two alternative "planning horizon" specifications. Thus, I assumed the planning horizon (i.e. T) ended at the 51st week (end of the observation period) in one specification. I assumed it was 100 instead of 51 in the alternative specification and reestimated the dynamic model[33]. It is worth noting that the goodness-of-fit of the dynamic model might be expected to increase with the length of planning horizon. This is so because as T increases, there is a higher payoff associated with sampling different brands for information purposes.

The parameter estimates and t-statistics of the static and dynamic structural models are shown in Tables 6 and 7, respectively. The results in Tables 6 and 7 suggest that the parameter estimates of the static and dynamic structural models are very similar. The price coefficient has the right sign (and is statistically significant). Consumers attach a high weight to the "latent" attribute level which I interpret as "quality" or "cleansing" power, but this weight is significant only at α=0.10. Most estimated mean attribute levels (A) also are not statistically significant.

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[32]The absolute amounts of the attribute levels do not have any meaning. Fixing one attribute level establishes the relative scale. I first assumed these to be 1. The optimization algorithm updates these values to ensure that the parameter estimates lie in the correct range of the utility function.

[33]This is done by forward extrapolation.

Table 6
Static Structural Model Estimates
(γ=0)

Parameter	Estimate	t-statistic
w_p	-0.790	-12.26
w_k	28.356	1.73
r	3.625	2.08
σ^2_{v0}	0.053	4.64
A_{Dash}	0.049	0.74
A_{Cheer}	0.019	0.27
A_{Solo}	0.056	0.84
A_{Surf}	0.105	1.65
A_{Era}	0.137	2.41
A_{Wisk}	0.040	0.59
A_{Tide}	0.138	.....
Φ_O	-17.657	-7.98
ψ_O	0.018	8.53
Φ_{NP}	-15.408	-6.99
ψ_{NP}	0.011	3.17
σ_δ	0.374	9.17
σ_ς	3.418	6.29
-LL = 7376.43	AIC = 7392.43	BIC = 7448.83

A few comments about these results seem to be in order at this point: 1) The value of zero does not have any absolute meaning for attribute level estimates, so a statistical test that suggests that these parameters are not statistically different from zero is not meaningful. Indeed, in studies of internal market structure such t-statistics are never reported. 2) The t-ratios are low because the standard errors are high. One reason for high standard errors is that one can easily scale the attribute levels up or down (along with corresponding changes in other model parameters) without substantially changing the

overall results. Thus, the model has some difficulty in estimating "absolute" levels of the latent attributes. 3) The covariances among the A's are high (which partly explains the relatively low t-statistics of w_k), hence, the differences among the attribute levels are indeed significant.

Table 7
Dynamic Structural Model Estimates

	T=100		T=51	
Parameter	Estimate	t-statistic	Estimate	t-statistic
w_p	-0.795	-12.31	-0.795	-12.28
w_k	34.785	1.84	32.689	1.76
r	4.171	2.25	4.026	2.16
σ^2_{v0}	0.040	4.21	0.042	3.89
A_{Dash}	0.040	0.74	0.043	0.74
A_{Cheer}	0.012	0.21	0.014	0.24
A_{Solo}	0.047	0.87	0.050	0.86
A_{Surf}	0.089	1.77	0.090	1.65
A_{Era}	0.120	2.64	0.120	2.44
A_{Wisk}	0.029	0.53	0.033	0.65
A_{Tide}	0.124	.....	0.120	.....
Φ_O	-17.267	-7.59	-18.778	-8.45
ψ_O	0.018	8.91	0.018	8.72
Φ_{NP}	-19.537	-8.55	-16.508	-7.46
ψ_{NP}	0.012	3.42	0.011	3.33
σ_δ	0.334	8.37	0.343	7.87
σ_ς	3.080	5.57	3.186	5.45
-LL = 7370.39 AIC = 7386.39 BIC = 7442.79			-LL = 7372.94 AIC = 7388.94 BIC = 7444.99	

Thus, the structural models differentiate the positions of brands in the attribute space. The results outlined in Table 6 and 7 suggest that Era and Tide have the highest level of

the attribute in question (i.e. cleansing power), while Cheer has the lowest amount of A[35].

The risk coefficient is significantly positive which indicates risk-averse behavior (Note that the sign of r was not constrained the sign of r). Thus, this result, combined with a positive w_k, indicates that perceived variance decreases utility and lowers brand choice probability. Thus, Proposition 2 is supported. I also was able to estimate the experience and advertising variabilities (σ_δ and σ_ς, respectively); both parameters are statistically significant, with advertising variability being much higher than experience variability. This result suggests that experience provides more information than advertising about laundry detergents. The initial variance (more precisely, the standard deviation) is significantly positive, but small, which is not surprising given that the laundry detergent market is a mature market in spite of new brand introductions etc.

The parameter estimates of the payoff functions suggest that the payoff associated with other brands and no purchase are increasing over time. This is so because over time consumers are learning about other liquids as well as powders brands (no purchase means that a consumer did not buy a liquid brand, s/he may have bought a powdered brand), perceived variance becomes smaller, and hence payoffs, increase over time. Although the constants of the payoff functions are negative, given the functional form of the utility function and these parameter estimates. "Utility" does not have any cardinal meaning in the proposed theory (only relative magnitudes are meaningful); hence, this does not imply

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[35]Indeed, these results have face validity. Tide is positioned as a high quality brand with superior cleansing power. Also according to the Consumer Reports (Weinberg and McDougall 1988), Tide has very high levels of active cleansing ingredients. On the other hand, Cheer, for example, is positioned as a "good value" brand.

any theoretical or methodological problems[36].

VI.2. Goodness of Fit

VI.2.1. In-Sample Fit

The log-likelihood (LL) for the calibration sample is -7463.23 for the GL model (Table 5). The log-likelihoods for the static and dynamic structural models are -7376.43, and -7370.39 (for T=100) and -7372.94 (for T=51), respectively (Tables 6 and 7). Table 5 and 6 report also AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). AIC is defined as:

$$AIC = - LL + R$$

where R is the number of parameters. Thus, AIC adjusts for the number of parameters estimated. BIC is defined as:

$$BIC = - LL + (1/2)\ R\ Log\ (N)$$

where N is the total number of observations. The structural models have the same set of parameters (16 in total) and the GL model has 15 parameters. N is 8517 (Sample size, i.e. 167, times the number of time periods, i.e., 51).

These results suggest that the GL model fits the data considerably worse than the structural models, especially when one considers that the LL values for the structural models are simulated values and they are downward biassed underestimating the goodness of fit. This is a rather surprising result because the structural models impose a lot of

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[36]Indeed, if one specifies a negative exponential utility function, one gets only negative utilities regardless of parameter estimates.

theory on the data and still fit the data better than GL. However, a "better" in or out-of-sample fit does not constitute the real value of structural models. Rather, the real value is associated with the fact that structural models explain processes. For example, the GL model does not explain how brand loyalty is formed, past purchases affect current choices (related to state dependence) or utility changes over time (non-stationarity). Both structural models, however, suggest that past purchases affect current choices because the experience associated with brands (information feedback) decreases perceived variance (risk) which increases utility (which causes utility to be non-stationary over time). Given risk-aversion, consumers tend to buy brands with which they have had positive experience. Hence, brand loyalty is an outcome of positive use experience. One may also suggest that brand equity is related to "perceived risk", however, brand equity exists regardless of use experience. For example, if perceived risk is decreased with advertising, brand equity will be high even if there is no prior experience with the brand.

The structural models also indicate that different purchase and advertising exposure histories create heterogeneity which is not endogenously accounted for in reduced form models. I tried to incorporate household characteristics to capture whatever additional heterogeneity was not captured, but these measures did not explain any residual heterogeneity. One key remaining issue is preference heterogeneity, however, this type of heterogeneity cannot be captured endogenously (one has to assume either a distribution of preferences or mass points associated with them. I have discussed this issue in Chapter V).

Thus, the structural models have considerably more "explanatory power" than the GL

model. One should not justify structural models on "fit" because they do worse in terms of "simplicity of use". For example, if one is only concerned, for example, with predicting aggregate market share, it may be still be useful to consult a model like the GL model.

So far, I contrasted the overall fit of the GL model with the structural models. Now I consider the differences between the structural models. First note that both structural models are estimated using simulation techniques, but in the dynamic model one also solves a dynamic programming problem in the dynamic model. As indicated before, the only theoretical difference between the two models is that the dynamic model takes into consideration the possibility that consumers may not maximize immediate utility and may sample brands for information purposes. All other theoretical issues are common to both of the models.

As previously indicated, the parameter estimates of the two models are very similar. The dynamic model fits the data slightly better than the static model. The dynamic model with T=100 specification fits the data better than T=51 specification as expected. As the two models are nested, the likelihood ratio test for nested models can be employed to see whether the difference in fit is statistically significant. The likelihood ratio value can be calculated as the following:

$$- 2 [LL_{STATIC} - LL_{DYNAMIC}] \sim \chi^2$$

The degrees of freedom of the χ^2 equals the number of parameters set to zero by nesting the static model within the more general dynamic model. The models differ in the discount factor (γ), which is set to zero in the static model. As previously indicated, the estimated γ parameter was 1.001 with a standard error of 0.02. When I set it to 0.995 and

estimated the model again, the parameter estimates were insensitive to it, and the log-likelihood was slightly worse (the log-likelihood improves with additional parameters estimated). Hence, I can use the likelihood ratio test as a conservative test to see if the difference in fit between the two models is statistically significant.

The difference in likelihood ratio values for comparing the fit of the two structural models is 6.98[37]. The critical value of χ^2 with 1 degree of freedom and at α=0.01 is 6.64 (α=0.05 equals 3.84). Thus, I reject the null hypothesis that the two models are the same: hence, the dynamic model fits the data better than the static model. However, although statistically significant, the difference in the fit is not "quantitatively" large. One possible reason for this may be that even if consumers do not maximize immediate utility (i.e. the dynamic model holds), the value associated with sampling brands as part of the information gathering process is not very high because the product category is mature. For example, consumers still sample brands for information when there are new brand introductions, but they already know quite a lot about different brands.

VI.2.2. Out-of-Sample Fit

To test the predictive validity of the models, I predicted the choices of the 48 households in my Springfield sample. Thus, the hold-out sample consisted of different households than those in the calibration sample. A predictive validity test based upon purchases of the same households in the calibration sample would be less stringent than

[37]I used the LL value of the dynamic model with T=51 specification. Note that this makes the test even more conservative because T=100 specification fitted the data better.

one based on a different set of individuals. The results of the out-of-sample validity test are reported in Table 8:

Table 8
Out-of-Sample Fit Test Statistics

Test Statistic	GL	Static Structural Model	Dynamic Structural Model	
			T=100	T=51
-LL	2000.69	1960.04	1961.64	1962.73
AIC	2015.69	1976.04	1977.64	1978.73
BIC	2059.21	2022.46	2024.06	2025.15

Both of the structural models predict the choices of the households better than the reduced form model (i.e. the GL model). The static structural model predicts slightly better than the dynamic structural model. The difference in fit is statistically significant at α=0.05 level and insignificant at α=0.01[38] when T=51. When T=100, the statistically significant difference (at α=0.05) between the static and dynamic models with respect to out-of-sample fit disappeared, Thus, goodness-of-fit of the dynamic model increased with the length of the planning horizon. However, I used the 51-weeks planning horizon in scenario evaluations because strategy simulations become computationally more difficult as T increases.

To summarize, both structural models outperform the GL model in terms of out-of-sample fit. I also calculated the predicted probability of a certain brand being chosen in

[38]The likelihood ratio value is 5.38.

each period. The results for Sioux Falls (the calibration sample) are reported in Table 9. Table 10 reports the calculated aggregate probabilities for Springfield.

Table 9
Aggregate Choice Probabilities
(Sioux Falls)

	Dash	Cheer	Solo	Surf	Era	Wisk	Tide	Other
Actual	0.0072	0.0114	0.0075	0.0223	0.0352	0.0409	0.0491	0.0666
GL	0.0075	0.0114	0.0074	0.0221	0.0361	0.0421	0.0502	0.0672
Static	0.0097	0.0113	0.0083	0.0198	0.0310	0.0484	0.0424	0.0670
Dynamic	0.0100	0.0119	0.0085	0.0208	0.0317	0.0496	0.0431	0.0674

The probability associated with "No Purchase" in the data is 0.7599. GL predicts it to be 0.7599, because the brand-specific constants in the MNL model guarantee perfect recovery of aggregate shares. Static and dynamic structural models predict it to be 0.7622 and 0.7570 respectively.

Table 10
Aggregate Choice Probabilities
(Springfield)

	Cheer	Surf	Era	Wisk	Tide	Other	No Purchase
Actual	0.0090	0.0049	0.0515	0.0310	0.0613	0.0739	0.7684
GL	0.0063	0.0056	0.0520	0.0346	0.0453	0.0700	0.7862
Static	0.0048	0.0011	0.0524	0.0306	0.0351	0.0708	0.8052
Dynamic	0.0053	0.0012	0.0533	0.0314	0.0354	0.0714	0.8020

The results in Table 9 and 10 indicate that the GL model predicts the aggregate choice probabilities better both in-sample and out-of-sample tests. This result is not surprising, because the brand constants in GL model adjust to capture the aggregate market shares. Thus, the model will fit the aggregate shares well without explaining them. For example, in the GL model, Dash has the lowest brand intercept whereas in the structural models Cheer has the lowest level of the attribute A. GL adjusts the brand constants to capture market share and as Dash's market share is the lowest, the brand constant is the lowest as well. On the other hand, structural models "explain" why the market share of Dash is the lowest: a low advertising frequency gives rise to a relatively high risk, rather than a low attribute level (the cleansing power of Dash is not the lowest among the attribute levels of other brands). Thus, GL model brand constants adjust according the market shares[39]. However, as I previously indicated, if the only relevant issue is to predict aggregate market share in the short-run, then GL model is a superior model to use.

VI.3. Scenario Evaluations

The parameter estimates obtained from the structural models can be used in simulation experiments to assess the impact of various strategy changes. Thus, the structural modelling approach enables me to do "scenario evaluations". Given the values

[39]Note that the A's of the structural models do not behave like brand intercepts. If one replaces the expected attribute levels in the expected utility function (Equation 7) by mean attribute level plus the expectation error (Equation 10), one sees that the A's are determined jointly with expectation errors and hence cannot adjust freely to reflect market shares.

of the estimated parameters, I randomly drew advertising and experience signals and prices to simulate choice outcomes (i.e., simulations described in Chapter III are repeated with empirical data and estimated parameter values). I varied the mean price, the advertising frequency, advertising, experience and price variability to assess their impact on brand choice (See Proposition 2 outlined in Chapter III). Figures 14-33 display a representative sample of my results. Each figure represents the impact of various strategy changes with respect to the aggregate choice probabilities associated with the brand "Surf"[40]. The simulation results also illustrate what happens to the aggregate choice probabilities of other brands if Surf changes its strategy. As well, one could run experiments in which two of the brands change their strategies. However, I focused on one brand because the results shown in these figures are representative of the types of strategy analysis one can do with structural models, and they show the direction of outcome changes given certain strategy changes for any brand. Unfortunately, however, experiments assume away all possible "reactions" from competitors, because I have to make the firms' actions endogenous in the theoretical model to be able to include competitor reactions. This is beyond the scope of this thesis.

- Insert Figures 14 - 33 about here -

In these figures, the X-axis is Time (51 **weeks**, where week 51 marks the end of the planning horizon in the dynamic model). The Y-axis is the aggregate choice probability

[40]The same type of analysis can be repeated with all brands under consideration. Indeed, I ran these experiments by varying Wisk's strategies, but because the main results are the same, I only report Surf results.

of Surf. Thus, the baseline (heavy lines) represents the aggregate choice probability associated with Surf in a given week prior the strategy change. The broken lines refer to the post-strategy case. I ran experiments for both structural models under two different conditions: 1) A "New Product" condition in which a brand with the same parameters (e.g., attribute level) of an actual brand like Surf was assumed to have been introduced in week 1[41], 2) a "Mature product" condition in which the brand under analysis is assumed to have been introduced before the calibration period, i.e., before week 1. Thus, in the "mature product" condition, past purchase and advertising exposure histories of households over the first two year period (not used as the calibration period) were taken into consideration. It should be noted that these figures show "spikes" that the simulations with fake data in Chapter III did not have. These spikes capture the weekly price movements. The results can be summarized as follows:

1) The higher the advertising frequency, the higher the brand choice probability, and this holds more for a "new product" than a "mature product". Furthermore, although the short run effect of advertising is not large, advertising has a strong cumulative effect on choice over time as it gradually reduces the perceived riskiness of a brand, which can be seen in results of both structural models (Figures 14-17). As well, advertising does not seem to affect brand choice much in the "mature product" case because competitors' actions are kept constant and there is no memory decay with respect to advertising in the model.

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[41]Note that Surf was introduced during the 1986-88 period, but before the first week of the calibration period.

2) Figure 18 and 19 show that lowering advertising variability increases choice probabilities, as hypothesized. Thus, a more consistent product positioning via advertising has a major positive impact on new product sales growth. In the "mature product" case the positive impact is very slight (Figures 20 and 21), but the dynamic structural model suggests that there is more impact than the static structural model. Thus, one might suggest that consistent product positioning via advertising is important for maintaining the market share of mature products.

3) Experience variability affects brand choice significantly in that lower variability increases choice probabilities; and this result holds for both the "New Product" and "Mature Product" case. The dynamic model suggests that the impact is larger than indicated by static model (Figures 22-25).

4) Price variability seems to have a slightly positive overall effect on choice because in the structural models price cuts constitute an incentive to consumers to try different brands (Figures 26-29). However, this result may not hold if one permits price to be a quality signal. In the latter case, the long-run impact of price promotions on consumer franchise can be assessed, which constitutes another area for future research.

5) Finally, I varied the mean price as an internal consistency check. Both models suggest that brand choice probabilities increase when the mean price is lowered (Figures 30-33).

6) The dynamic structural model suggests that consumers are more willing to try new brands than suggested by the static structural model (See the baseline for the two models in "New Product" condition); therefore, the dynamic model reveals a slightly higher

consumer sensitivity to the marketing mix.

These results are very straightforward. They provide support for Proposition 2 described in Chapter III[42]. The scenario evaluations also suggest that structural modelling approaches that incorporate at least the impact of the "past" on choice can give valuable long-run strategy implications. Reduced form models cannot capture any long-term impacts of strategy changes, whereas a structural model can. For example, my results indicate that advertising has a cumulative long-run effect although the short run impact is very small.

The results also reveal that the two structural models produce very similar results when applied to a product category like laundry detergent because the additional value gained by sampling different brands would not be large in this market if consumers already know quite a lot about laundry detergents. Thus, in the case of mature product categories, it may well be that a structural model that assumes immediate utility maximization can capture most of what a more complicated "dynamic" structural model captures.

[42]These simulations show that choice probabilities increase in advertising frequency, lower advertising and experience variability. By definition, experience with a brand increases the choice probability given a statistically significant experience variance (estimated as standard deviation) parameter estimate and a statistically significant initial (perceived) variance parameter estimate.

CHAPTER VII

DISCUSSION AND CONCLUSIONS

VII.1. General Discussion

This thesis accomplished three purposes. First, it introduced a comprehensive signalling framework within which the relations and dependencies among consumer risk, consumer information search, firms marketing mix activities, consumer brand choice and brand values under imperfect and asymmetric information can be understood and analyzed.

Second, taking firms' actions to be exogenous and focusing on the direct information value of consumption experience and advertising, the impact of the "past" (i.e., past purchases and advertising) and the "future" (information value of choices affecting current choices) on the choice process was captured by adopting a structural modelling approach.

Third, two structural models and an approximation to a reduced form model were estimated to test the proposed theory. The results suggested that capturing "choice dynamics" with reduced form models may give rise to misleading conclusions like the absence of advertising effects. Furthermore, models like mulitinomial logit with lagged purchases do not explain behavior because they do not address questions like how brand loyal behavior occurs. Both structural models, however, are based upon behavioral theory, and hence explain "processes". Results also showed the "dynamic" model to be significantly different than the "static" model. Thus, even in a mature market like laundry detergent market, consumers may not maximize immediate utility. However, in terms of

predictive validity, the static model that captured only the effects of the "past" performed at least as well as the "dynamic" model that captured both "past" and "future" effects of the brand choice process in liquid laundry detergent category.

VII.2. Theoretical and Methodological Contributions

This thesis contributes to the understanding of brand choice dynamics under imperfect information. It shows that structural approaches can be better ways to explain choice processes. This latter result has a number of implications for brand choice and panel data research.

Structural approaches properly distinguish variation across and within households over time. Even more recent attempts to differentiate between these two sources of variation adopted approximations to reduced form approaches to separate the two types of variation using statistical procedures that do not explain behavior (e.g., Fader and Lattin 1992). The structural models proposed in this thesis suggest that across household variations (e.g., preference heterogeneity) and within household variations over time (e.g., non-stationary utility because perceived risk is updated in each period) are two different, but possibly related types of variation. For example, heterogeneity in experience and past advertising exposures (endogenous observed heterogeneity) and in perception errors (endogenous unobserved heterogeneity) cause variation among households, but at the same time these past experience / advertising signals and serially correlated perception errors create state dependence (past histories affect current choices). Thus, the proposed theory and modelling approach have implications for consumer learning, brand loyalty and brand

equity. State dependence may result from learning which should be separated from brand loyalty. Brand loyalty or steady-state equilibrium repeat buying behavior occurs because of low riskiness of relevant brands, given a good fit between brand attributes and individual tastes. Because different consumers may have different purchase histories, they may have different levels of perceived brand risks. Thus, past behavior (having experience with a particular brand) alters current behavior (experience lowers risk and increases the probability of repeat buying, *ceteris paribus*, i.e. keeping consumer preferences constant); and brand loyalty is formed over time via positive use experience (state dependence). However, brand loyalty cannot be reduced to state dependence even if one controls for unobserved heterogeneity because state dependence may be caused by factors (e.g. learning) other than brand loyalty related factors.

An implication of this thesis research for brand equity is that the additional utility not explained by brand attributes is created by low risk levels (along with possibly reduced information costs as shown in Appendix 1) which gives rise to brand loyal behavior.

Furthermore, the "dynamic" structural model recognizes the influence of current choices on the information sets of consumers, and consequently on future expected utilities, as well as the impact of future expected utilities on current choice behavior. Thus, unlike previous research on choice dynamics, the proposed formal dynamic model is forward-looking. The results indicate that this model will be most useful in categories where there is a lot of uncertainty and learning.

This thesis also constitutes the first application of the Keane and Wolpin (1992) approach to solving and estimating dynamic structural models. The empirical results

suggest that the Keane and Wolpin approach makes it feasible to test dynamic structural models that involve complex patterns of time dependencies.

My structural modelling approach applied to both the "static" and "dynamic" models proposed in this thesis also may be useful in analyzing the impact of marketing mix activities on brand choice. This thesis focused only on the impact of individual advertising signals on brand choice and showed that consistent (low variance) advertising may create brand loyalty. In contrast, previous research with static models like Tellis (1988) found that brand loyalty acts as a moderator variable with respect to the impact of advertising on brand choice, i.e., brand loyalty increases advertising effectiveness.

Although I do not analyze the impact of sales promotions on brand choice *per se* in this research, my modelling approach may be useful for studying the impact of promotions on brand choice. For example, the analysis of various factors that underlie sales increases during the promotion period is an important research issue in marketing (e.g., Gupta 1988, Neslin and Shoemaker 1989). Because my modelling approach produces policy-invariant parameter estimates, it can differentiate among factors (e.g., brand-switching, purchase time acceleration) that may underlie the sales increases during the promotion period. For example, the impact of price promotions on consumer franchise can be analyzed within a structural modelling framework once price as a quality signal is integrated into the model.

VII.3. Future Research

There are a number of issues that are left for future research in this thesis. In the context of panel data research, one obvious task will be to compare the two versions of the structural models using different product categories. One may expect that the results generated by the two models will diverge more when there is more uncertainty and learning during the process of choice. For example, with respect to scanner panel data, one may expect more consumer uncertainty and learning in "disposable diapers" category.

The models can be used to analyze new product introduction processes. One also may be able to use these models to investigate choice processes associated with products and services that show inherently more experience variability (e.g. restaurants, airline services etc.). Thus, I want to design experiments to study choice contexts in which there is inherently more uncertainty and learning. Experimental research also will allow me to manipulate the precision of various information signals. Within the context of the structural models proposed in this thesis, this enables me to explicitly investigate issues such as advertising copy effects and how consistent positioning can be achieved via advertising.

As far as the theoretical modelling approach is concerned, a number of extensions can be made. First, within the context of scanner panel research, I want to allow for heterogenous weights (preferences and market responses) to see how much unexplained unobserved heterogeneity is left after one endogenously accounts for heterogeneity. Second, I want to integrate price in the structural models as a quality signal. This will enable me to investigate the long-run impacts of price promotions, for example, on

consumer franchise. Third, advertising signals may "create" attribute dimensions (e.g. stylishness). Fourth, one may relax the assumptions that mean attribute levels and preferences are constant over time. Appendix 1 describes how to account for the former in the structural models. The latter can be incorporated in the model by allowing advertising to affect utility weights. However, I expect the estimation of such a model to be extremely difficult.

The structural modelling approach can be applied to the process of forming price expectations. I want to investigate how the frequency and intensity of price promotions affect consumer expectation about mean prices. Structural models also can be extended to account for variety seeking. Finally, the inventory behavior has to be incorporated endogenously in the model, and then quantity choice can be modelled as well. In this context, an approach similar to that in Gönül and Srinivasan (1991)[42] can be adopted.

The structural models developed and tested in this thesis took product category choice as given. The dynamic structural model can be modified and adopted to capture innovation diffusion processes. The value of information contained in each choice alternative drives the dynamics in the dynamic structural model discussed in Chapter III. When product category choice is not given and the product in question is a new product, the choice problem becomes whether to buy the product and if so, when to buy it. This problem can be modelled as an intertemporal choice problem: the longer the consumers defer buying a product, the more information they can gather but they forego the utility of buying and using the product. Thus, a dynamic model of an innovation process would

[42]They modelled coupon expectations using a structural model.

suggest that consumers think about how much information they can get in each period and assess the value of that information. They also think about how much utility they forego by not buying the product in each period, and consequently determine an optimal strategy. In each period they decide whether to continue to search for information and whether they to buy the product or not. At the end of each period, they may decide to gather more information or buy the product. Formally, this problem can be solved by adopting the dynamic programming approach. Unlike the dynamic structural brand choice model, such a model yields an optimal stopping rule. Furthermore, this model differs from brand choice models in that it will not have experience signals, but will incorporate active information search: hence, the cost of getting an information signal has to be introduced into the model. Also, word of mouth can play a role, and the probability of getting a word of mouth signal should increase over time (there will be more adopters as time passes). This type of model can enable researchers to asses the impact of alternative marketing strategies on the diffusion process.

Figure 1.a

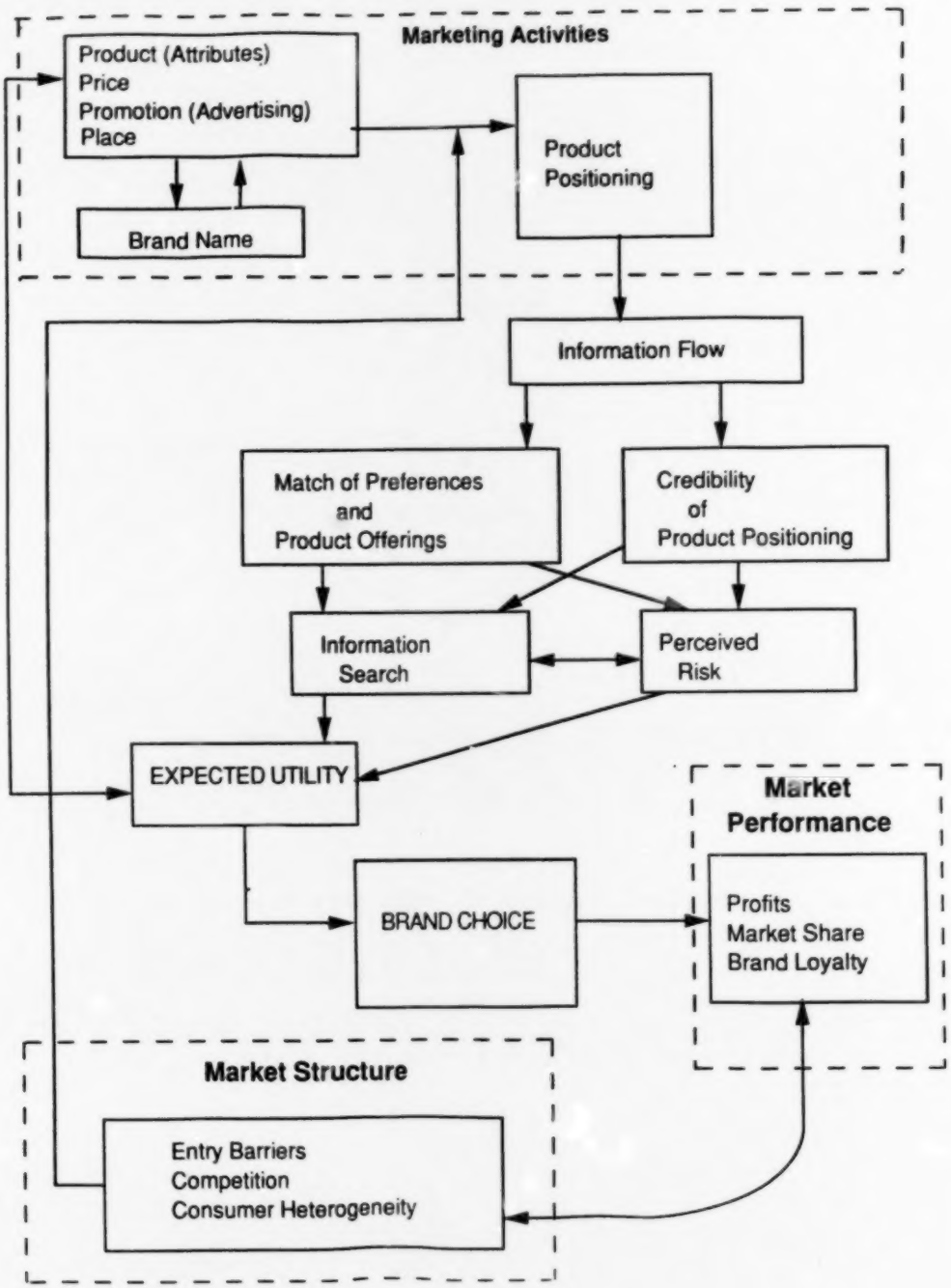

Marketing Activities
Product (Attributes)
Price
Promotion (Advertising)
Place
Brand Name
Product
Positioning
Information Flow
Match of Preferences
and
Product Offerings
Credibility
of
Product Positioning
Information
Search
Perceived
Risk
EXPECTED UTILITY
Market
Performance
BRAND CHOICE
Profits
Market Share
Brand Loyalty
Market Structure
Entry Barriers
Competition
Consumer Heterogeneity

Figure 1.b

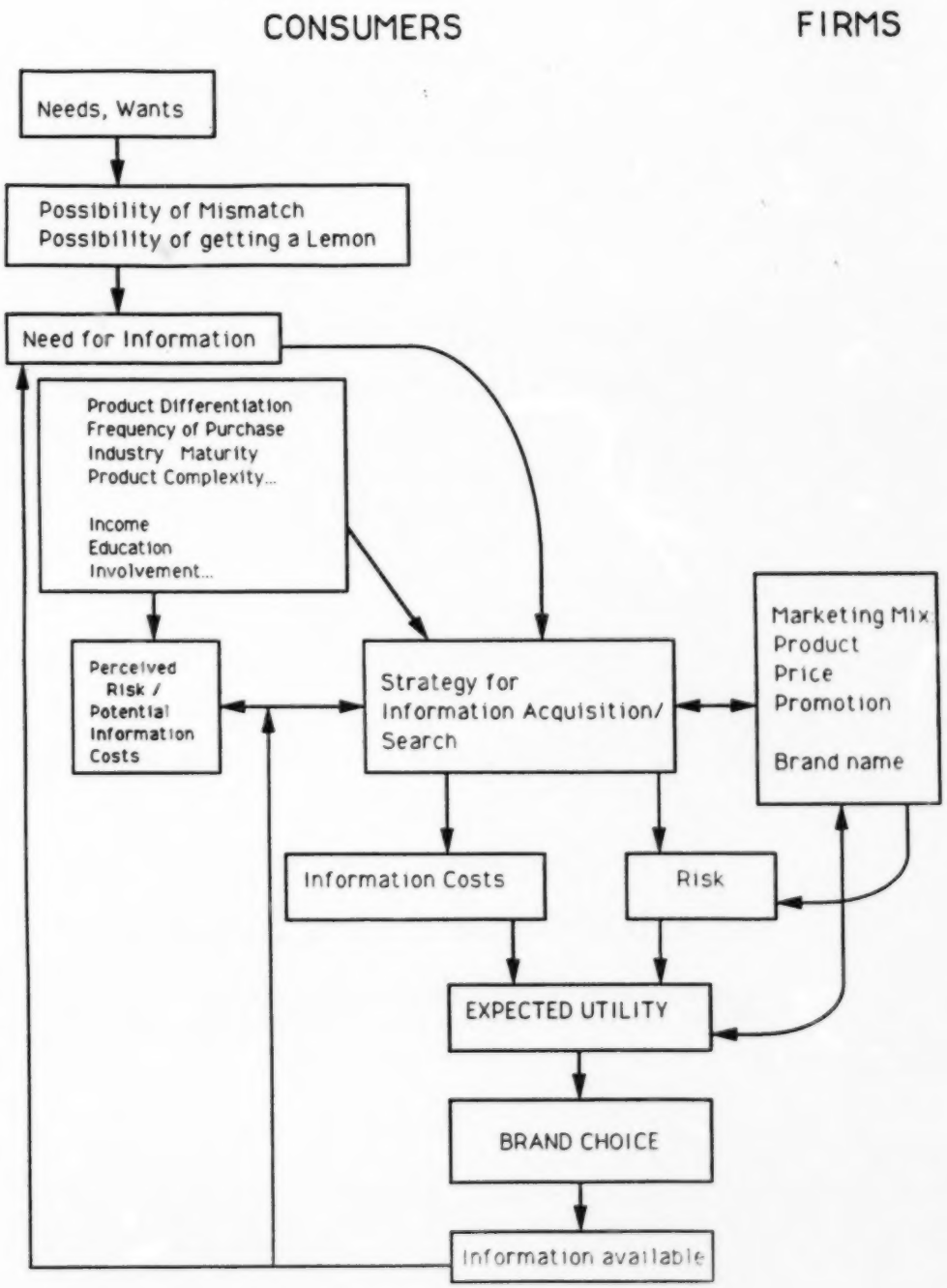

CONSUMERS
FIRMS
Needs, Wants
Possibility of Mismatch
Possibility of getting a Lemon
Need for Information
Product Differentiation
Frequency of Purchase
Industry Maturity
Product Complexity...
Income
Education
Involvement...
Perceived Risk / Potential Information Costs
Strategy for Information Acquisition/ Search
Marketing Mix
Product
Price
Promotion
Brand name
Information Costs
Risk
EXPECTED UTILITY
BRAND CHOICE
Information available

Figure 2

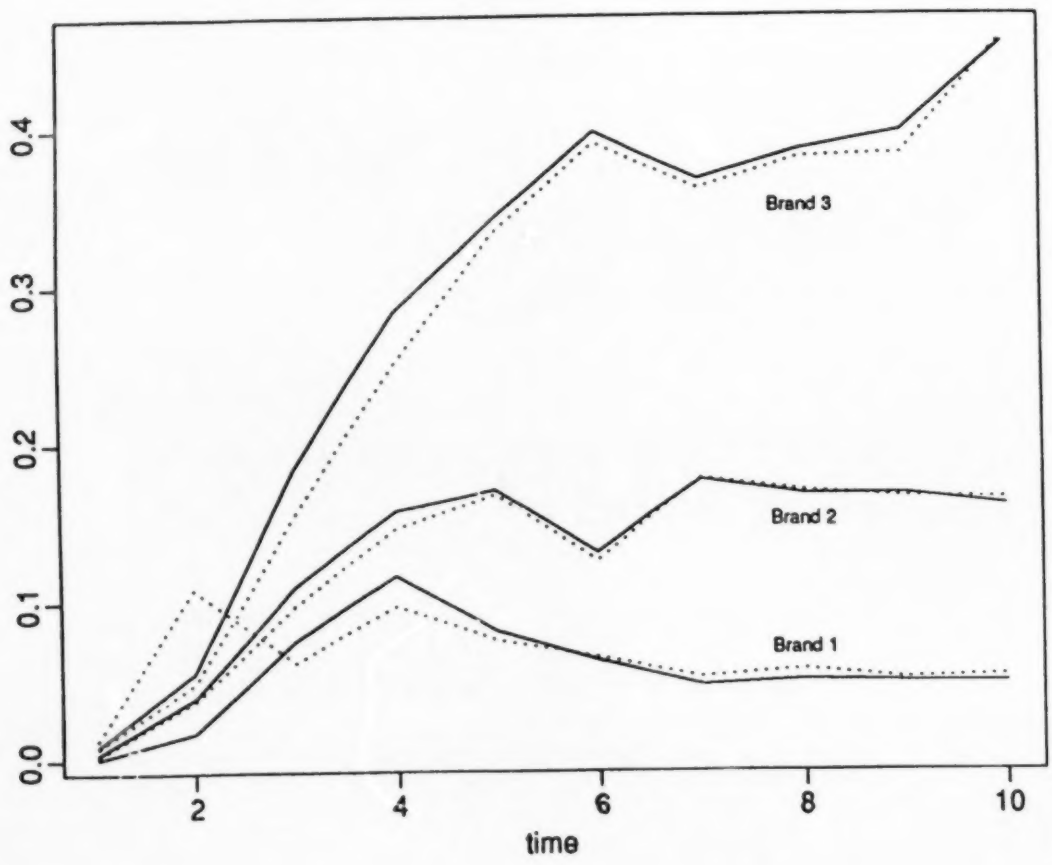

Firm 1 decreases price from $ 10 to $ 5 in periods 1 and 2
Brand 3
Brand 2
Brand 1
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time

Figure 3

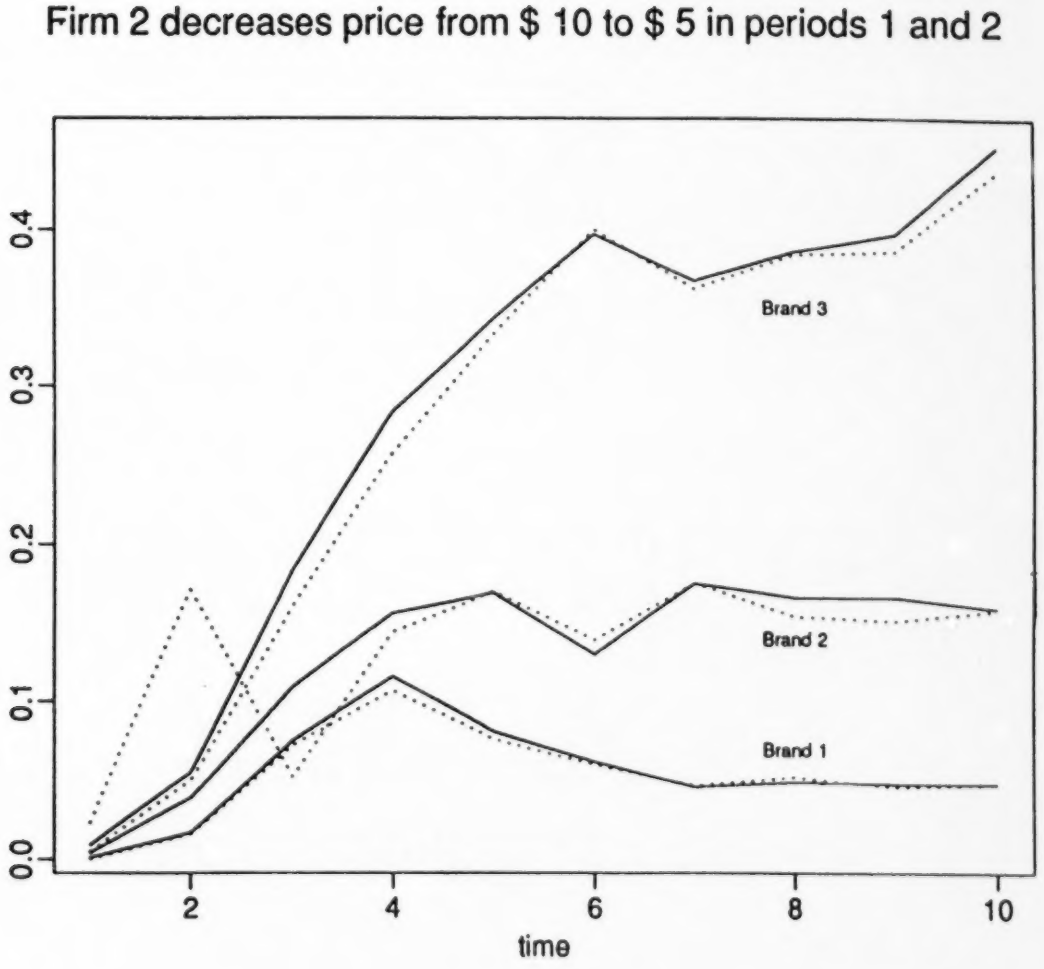

Firm 2 decreases price from $ 10 to $ 5 in periods 1 and 2
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figure 4

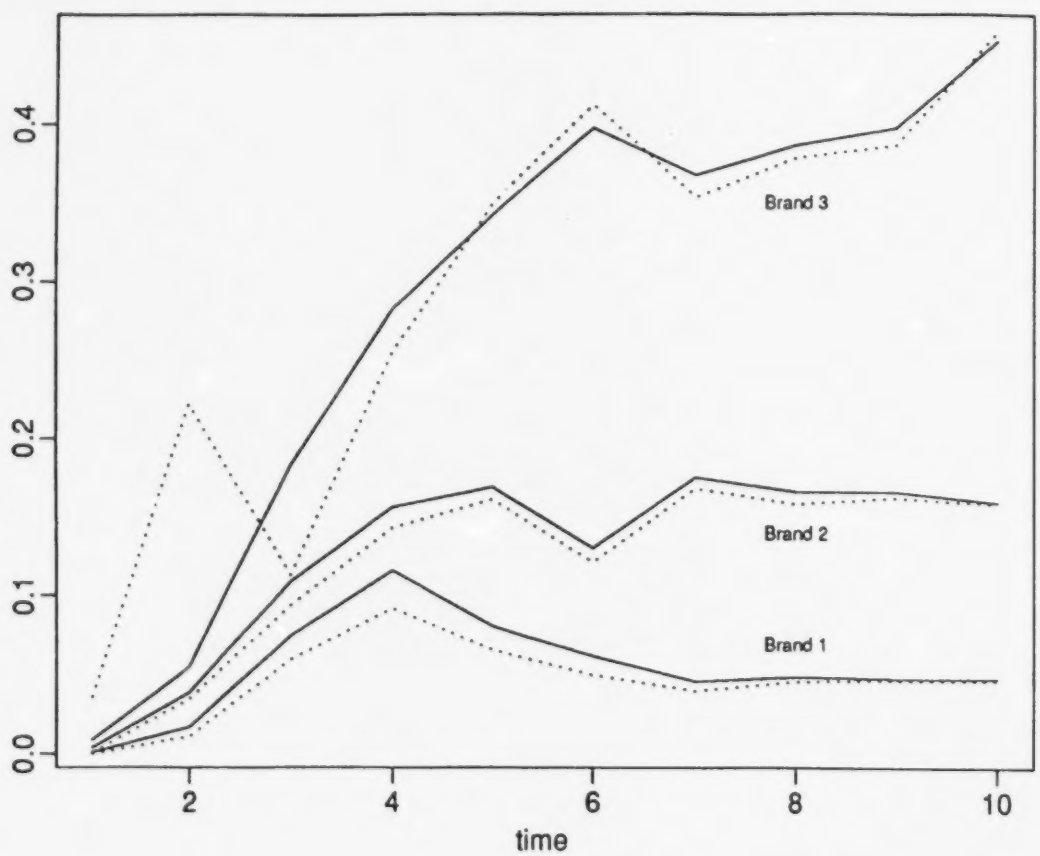

Firm 3 decreases price from $ 10 to $ 5 in periods 1 and 2
Brand 3
Brand 2
Brand 1
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time

Figure 5

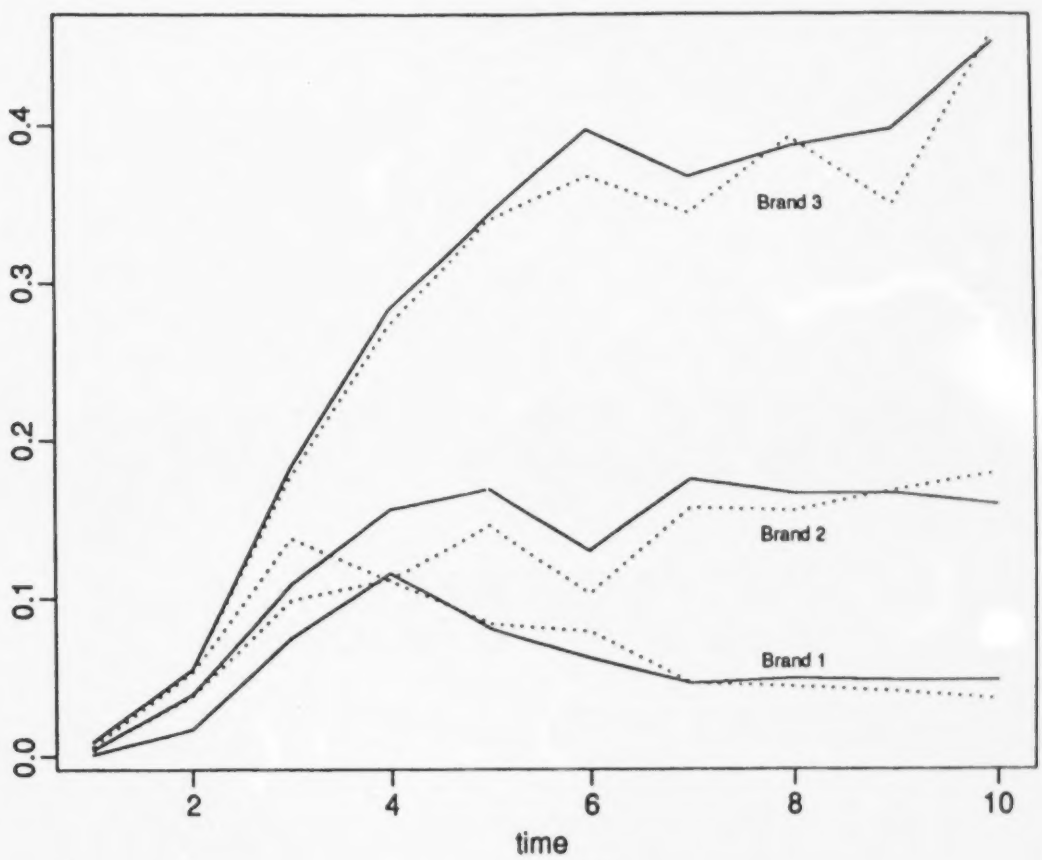

Firm 1 increases advertising frequency from 20% to 60%
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figure 6

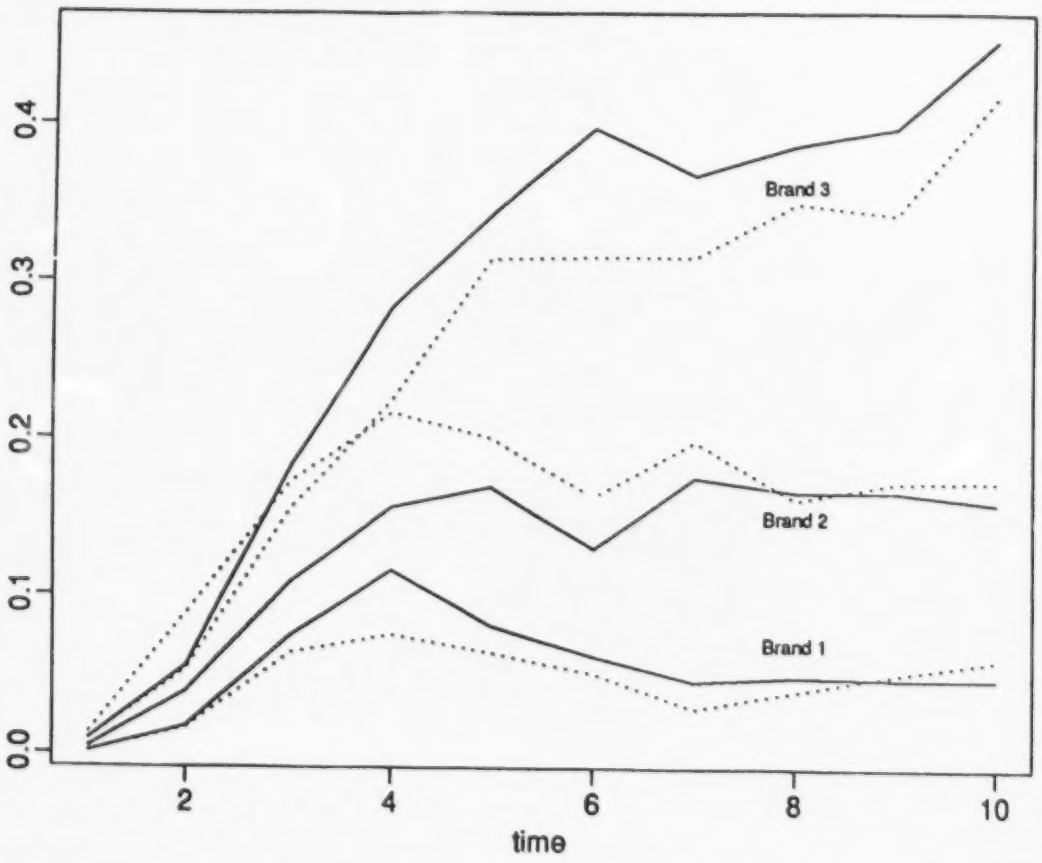

Firm 2 increases advertising frequency from 20% to 60%
Brand 3
Brand 2
Brand 1
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time

Figure 7

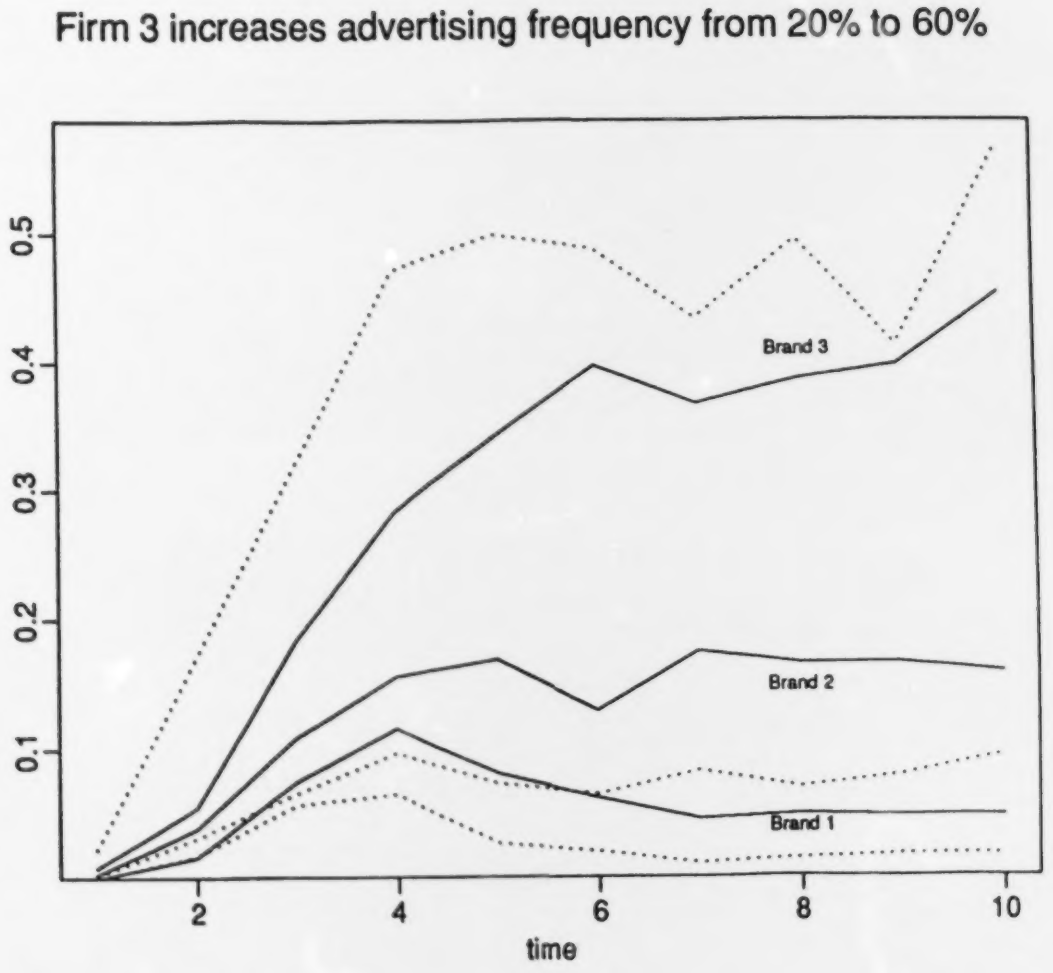

Firm 3 increases advertising frequency from 20% to 60%
0.1
0.2
0.3
0.4
0.5
Brand 3
Brand 2
Brand 1
2
4
6
8
10
time

Figure 8

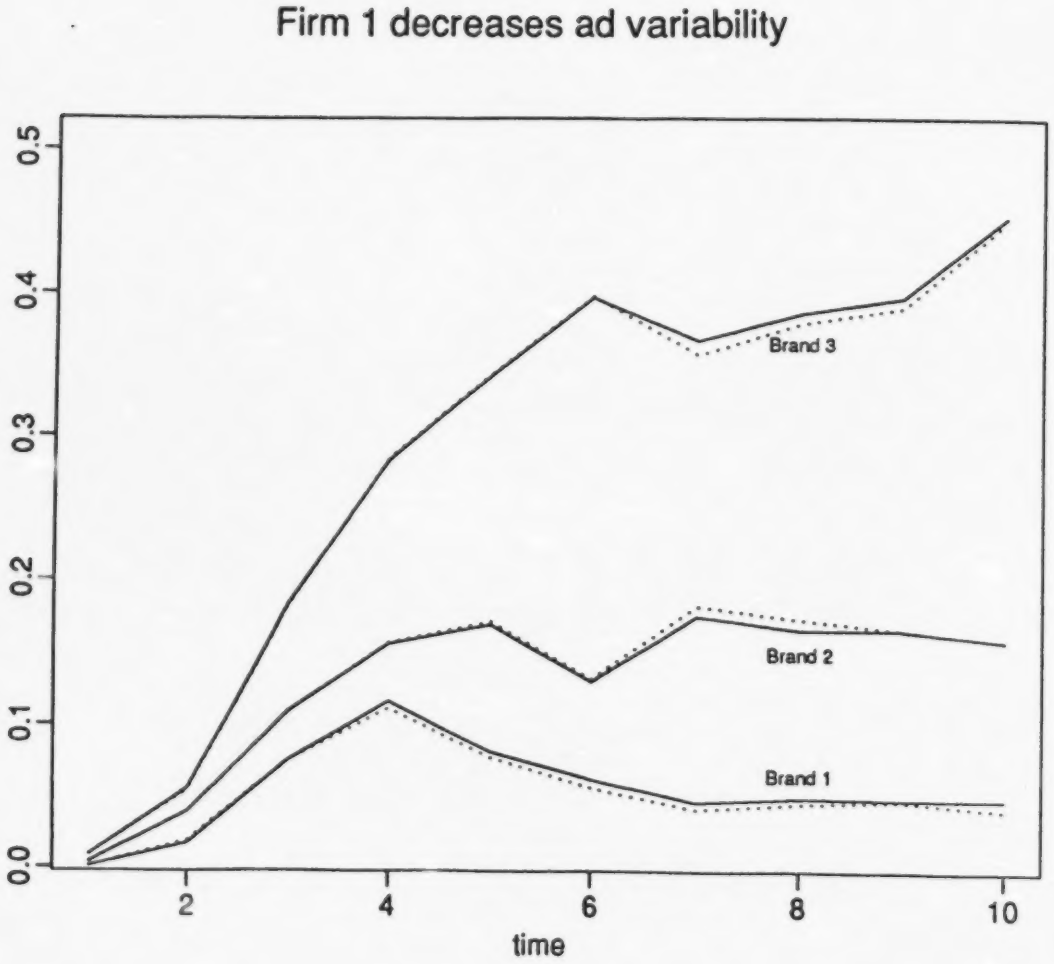

Firm 1 decreases ad variability
0.0
0.1
0.2
0.3
0.4
0.5
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figure 9

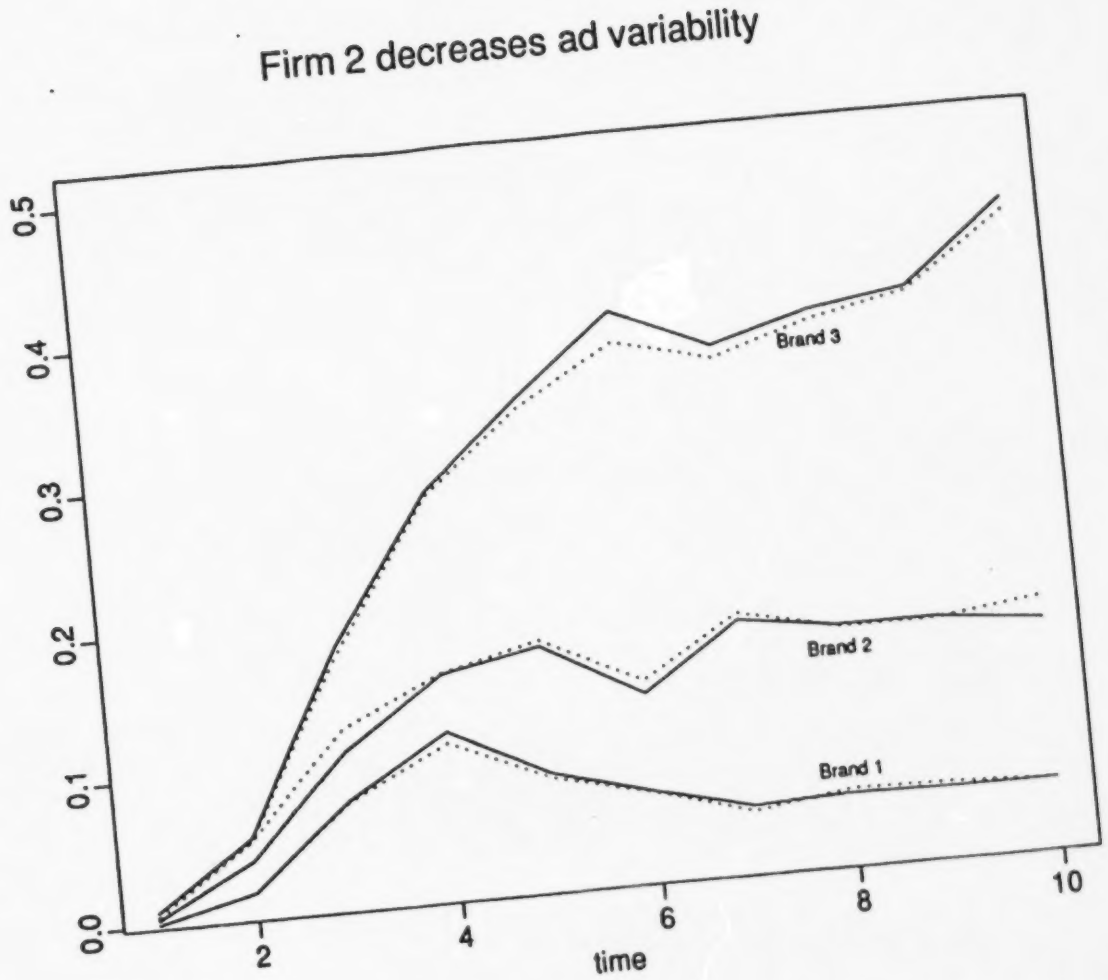

Firm 2 decreases ad variability
0.0
0.1
0.2
0.3
0.4
0.5
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figure 10

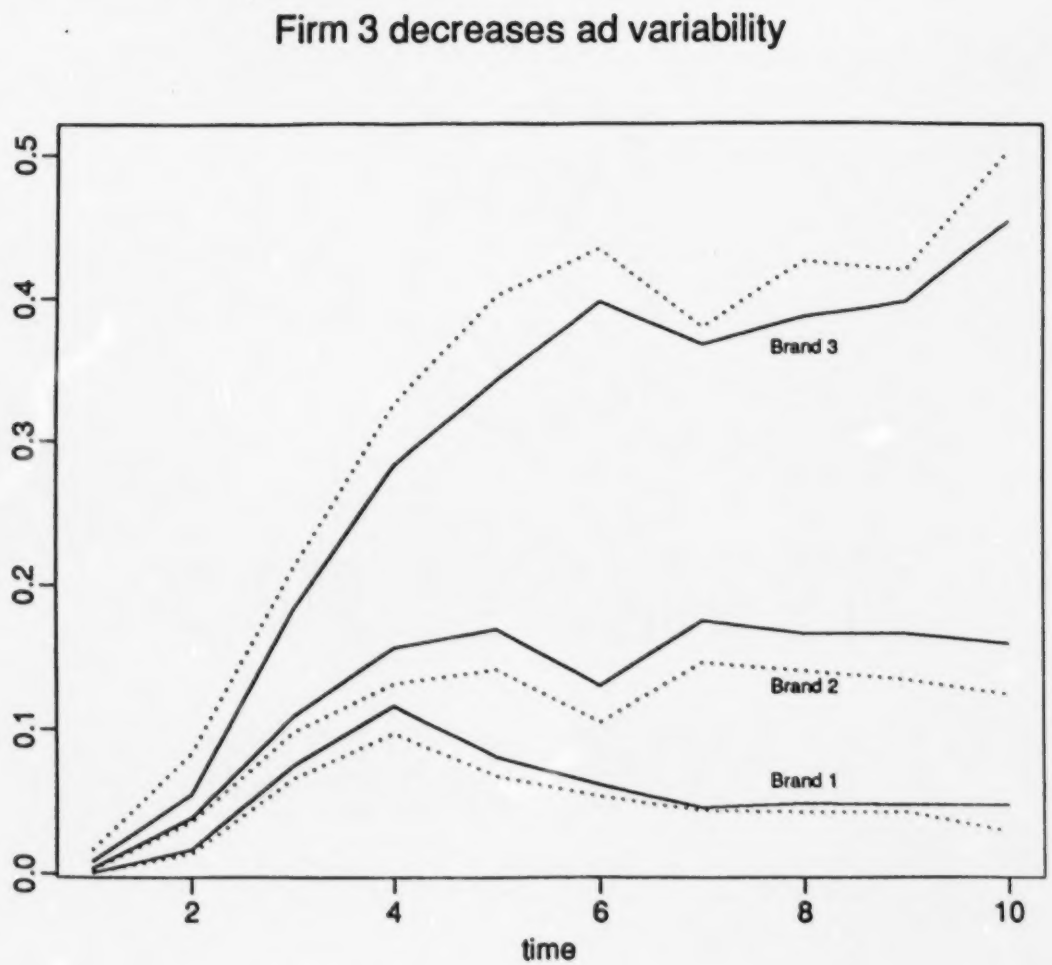

Firm 3 decreases ad variability
0.0
0.1
0.2
0.3
0.4
0.5
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figure 11

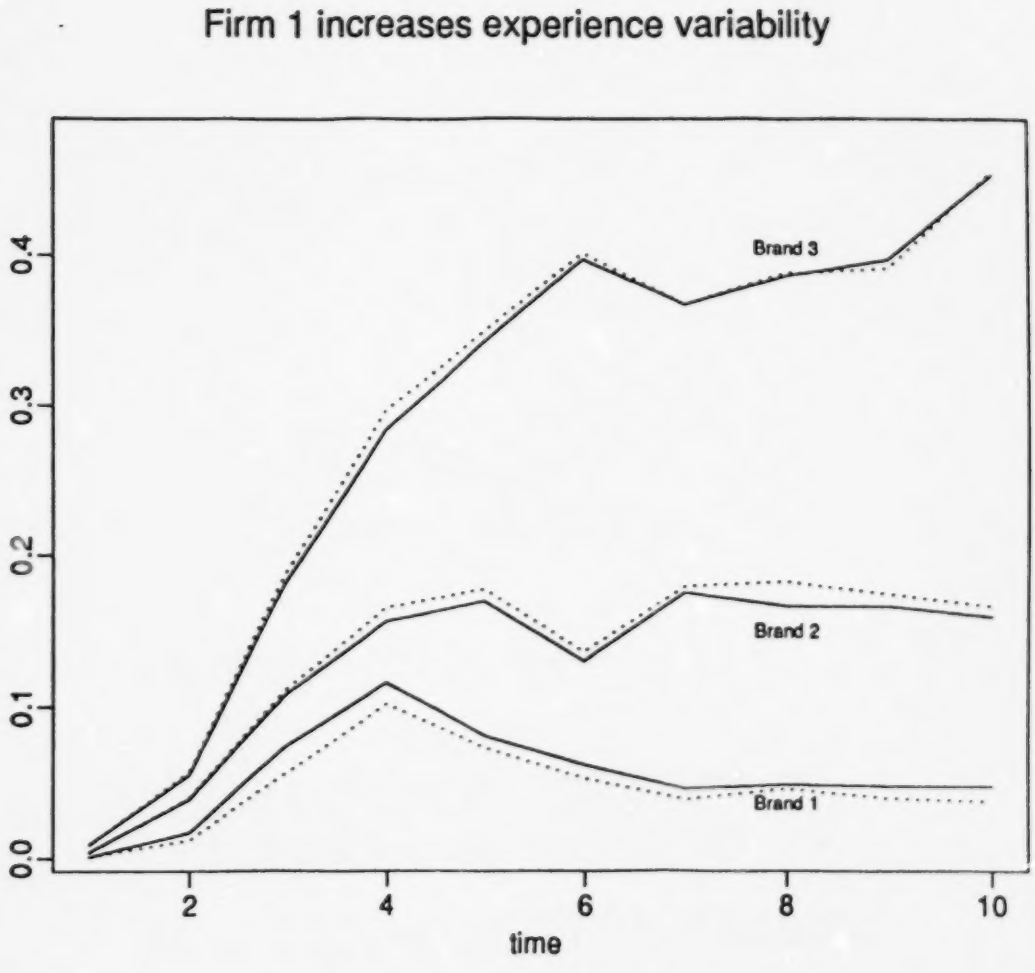

Firm 1 increases experience variability
Brand 3
Brand 2
Brand 1
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time

Figure 12

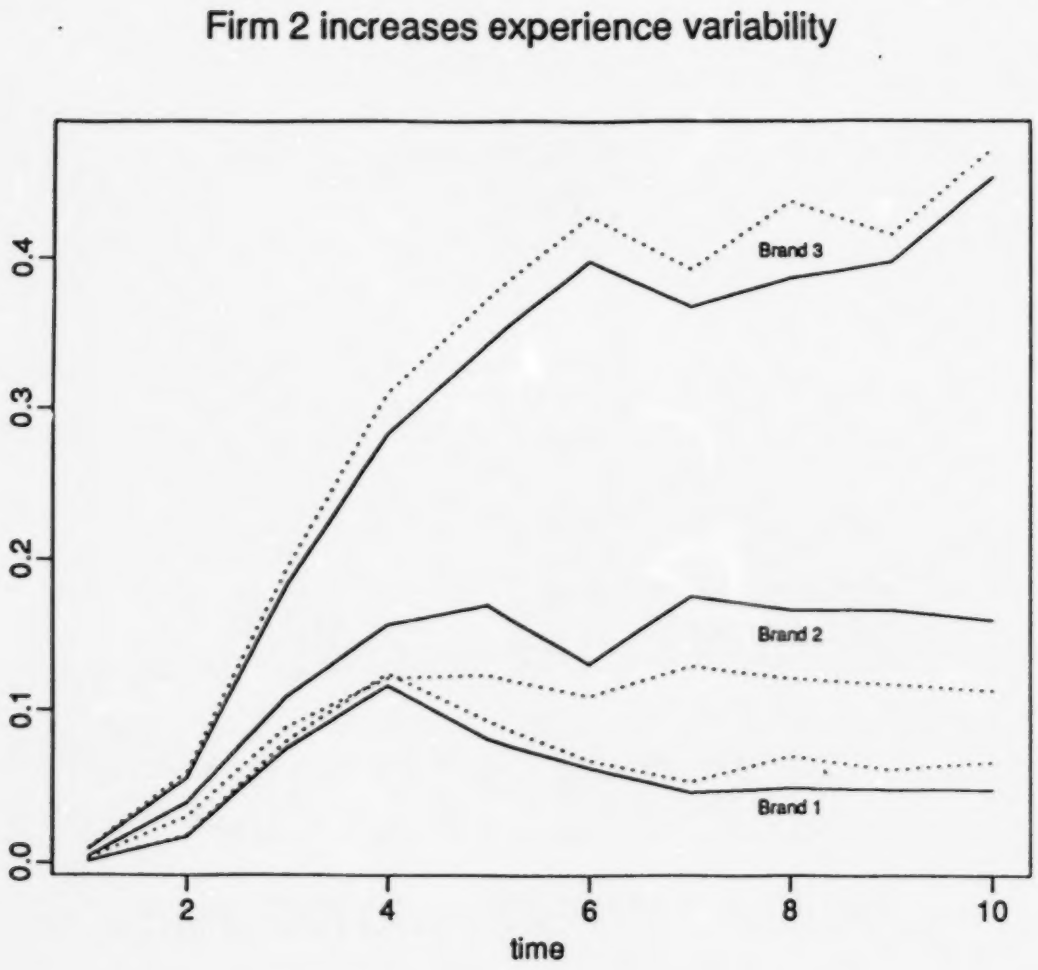
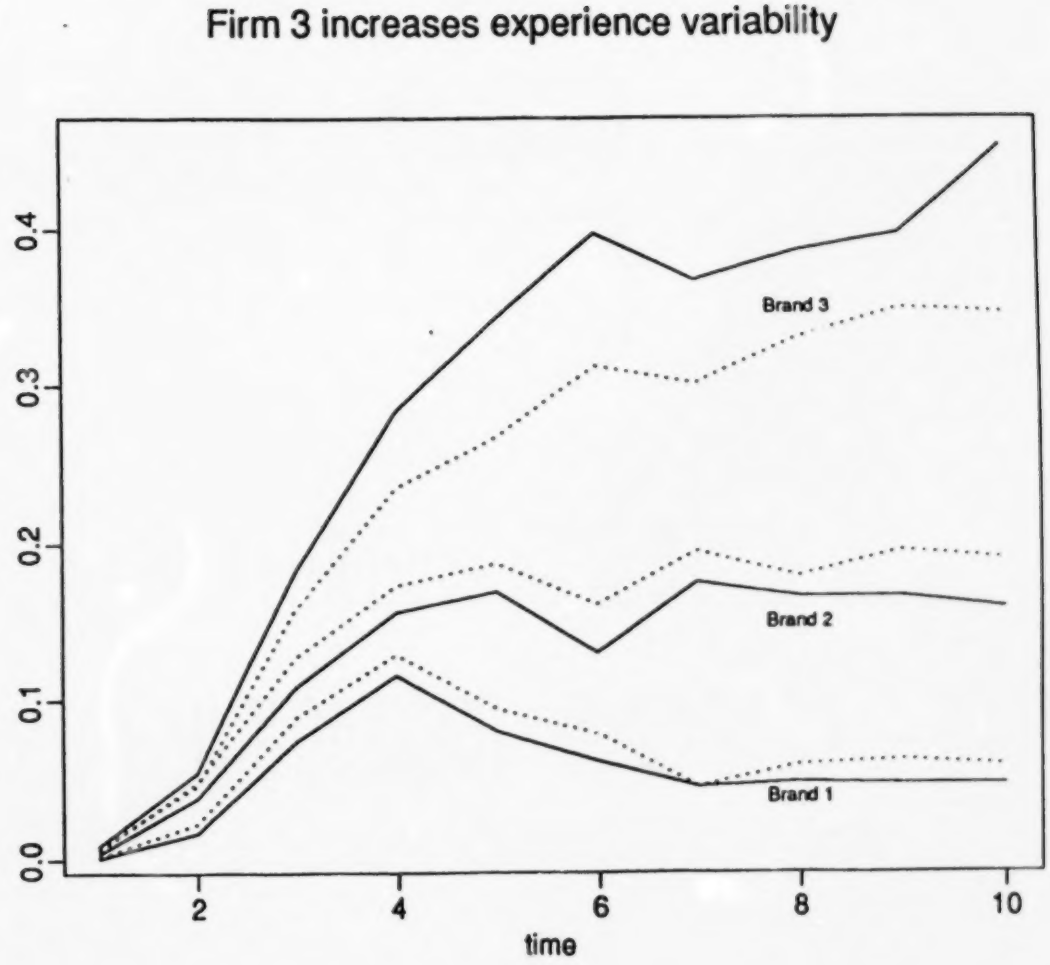

Firm 2 increases experience variability
Brand 3
Brand 2
Brand 1
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time

Figure 13


Firm 3 increases experience variability
0.0
0.1
0.2
0.3
0.4
2
4
6
8
10
time
Brand 3
Brand 2
Brand 1

Figures 14 and 15

Fig. 14: Surf Increases Ad Frequency from .234 to .700
(Static / New Product)

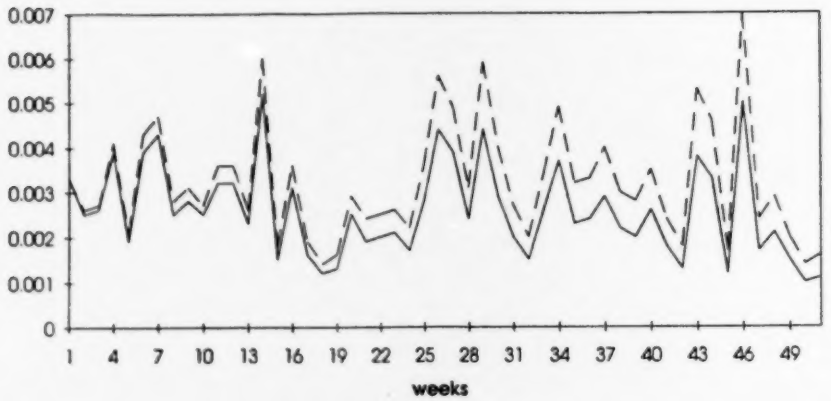
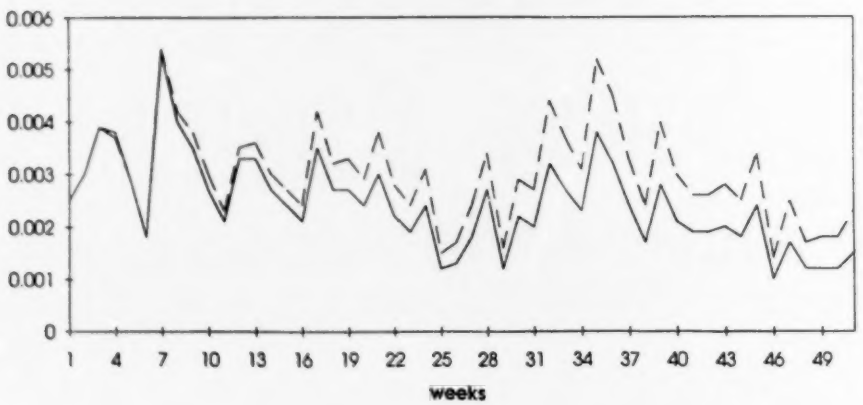


Fig. 15: Surf Increases Ad Frequency from .234 to .700
(Dynamic / New Product)



Figures 16 and 17

Fig. 16: Surf Increases Ad Frequency from .234 to .700
(Static / Mature Product)

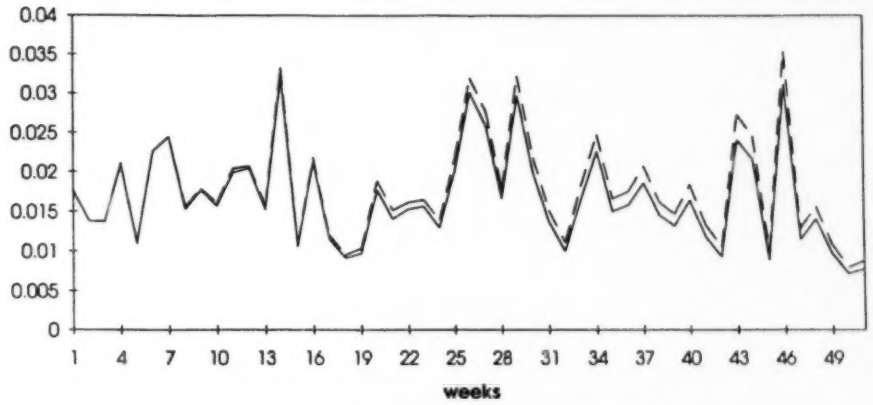
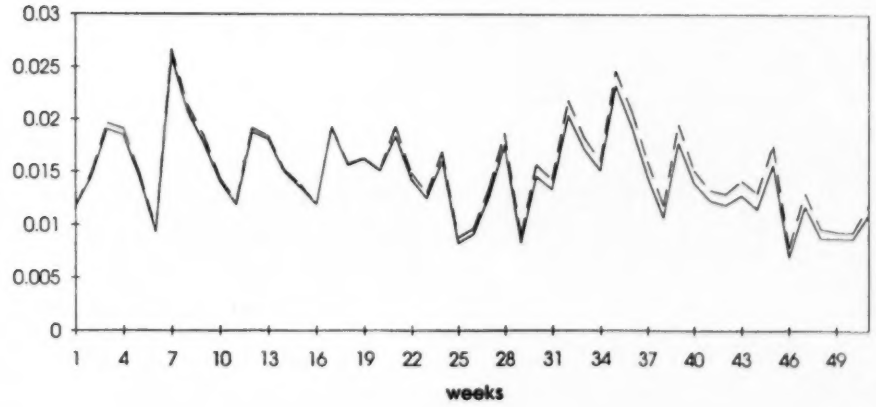


Fig. 17: Surf Increases Ad Frequency from .234 to .700
(Dynamic / Mature Product)



Figures 18 and 19

Fig. 18: Surf reduces Ad Variability by 50 %
(Static / New Product)

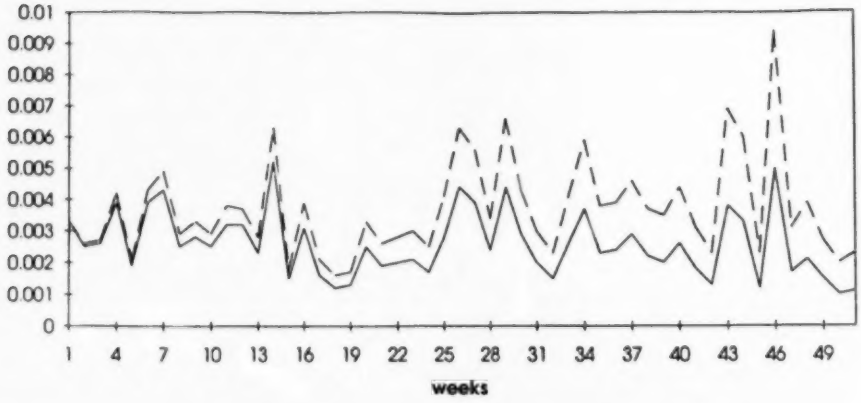
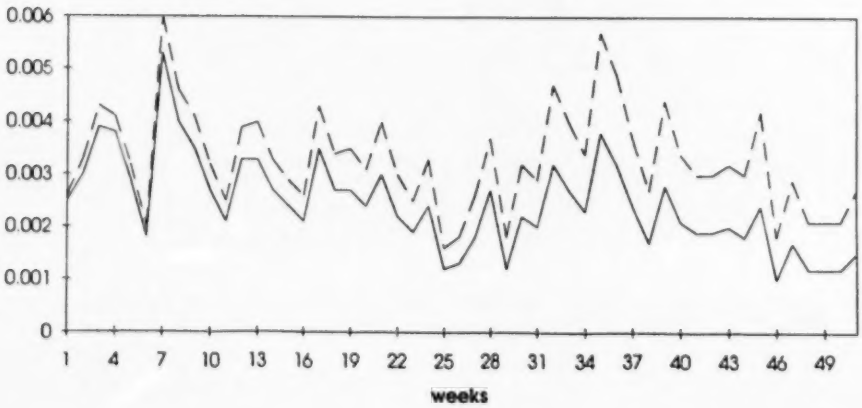


Fig. 19: Surf reduces Ad Variability by 50 %
(Dynamic / New Product)



Figures 20 and 21

Fig. 20: Surf reduces Ad Variability by 50 %
(Static / Mature Product)

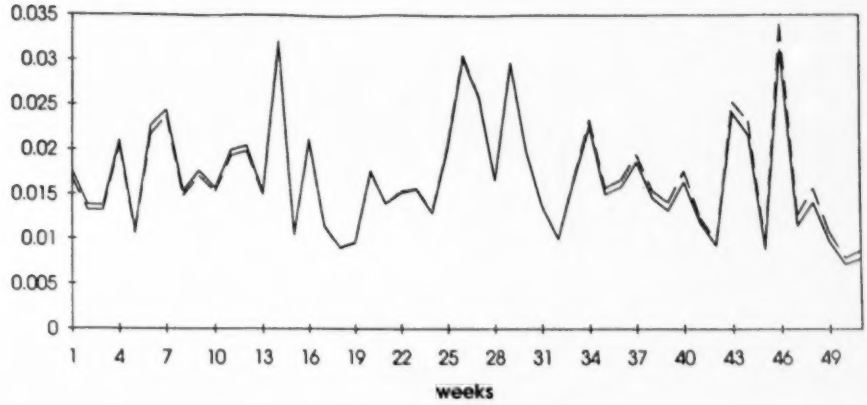
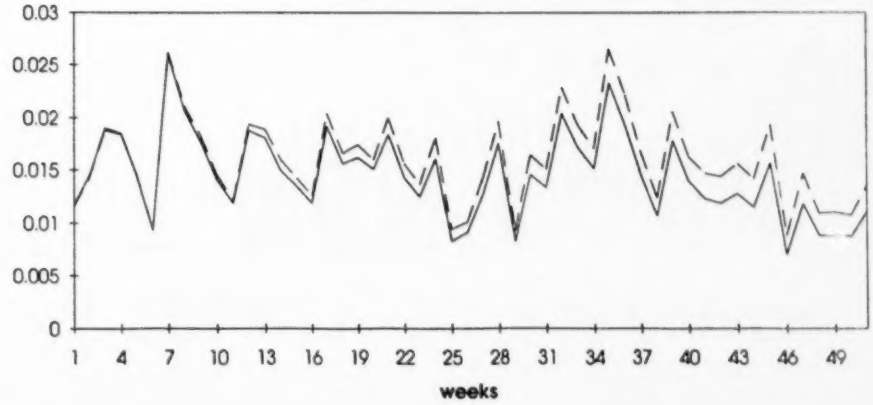


Fig. 21: Surf reduces Ad Variability by 50 %
(Dynamic / Mature Product)



Figures 22 and 23

Fig. 22: Surf reduces Experience Variability by 5 %
(Static / New Product)

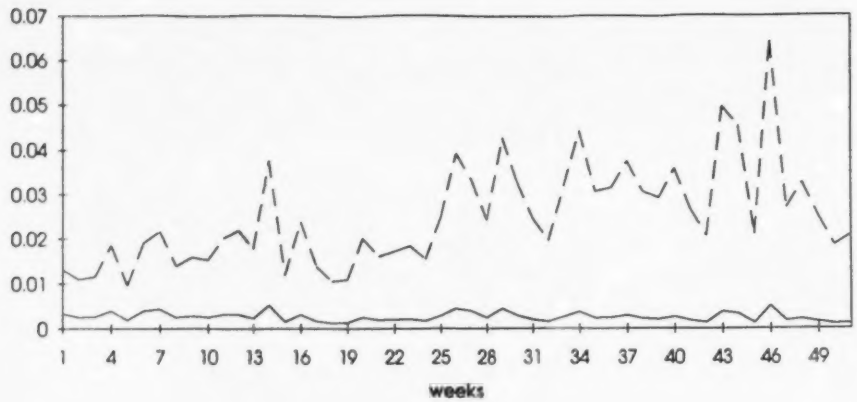
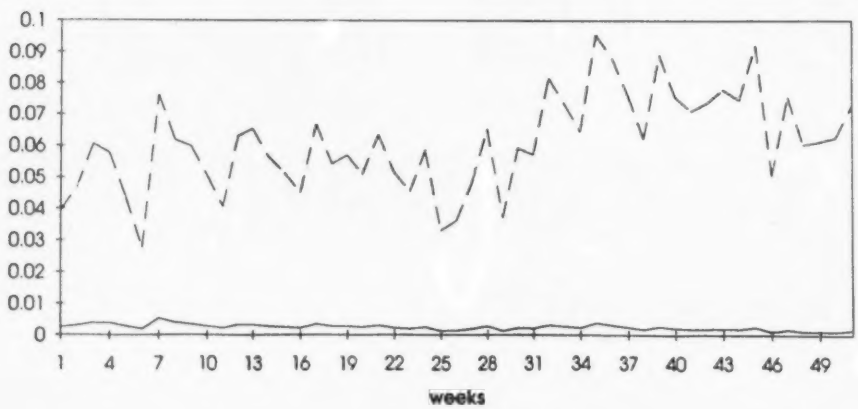


Fig.23: Surf reduces Experience Variability by 5 %
(Dynamic / New Product)



Figures 24 and 25

Fig. 24: Surf reduces Experience Varaibility by 5 %
(Static / Mature Product)

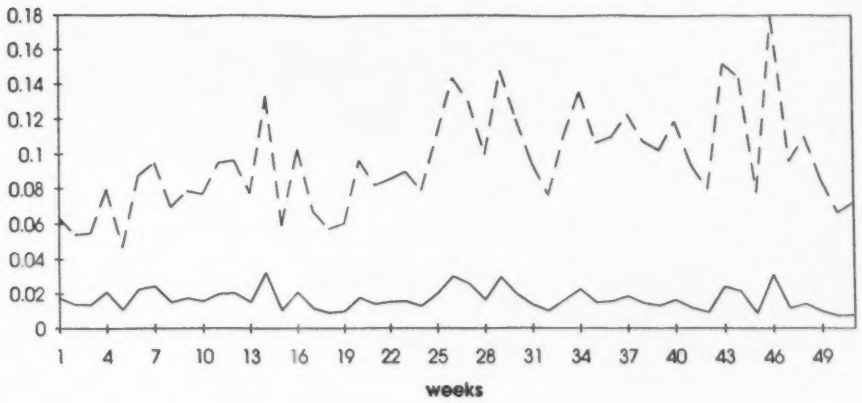
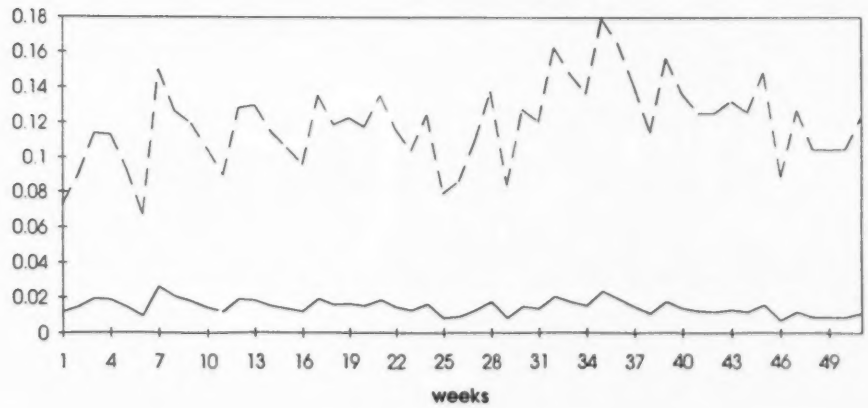


Fig. 25: Surf reduces Experience Variability by 5 %
(Dynamic / Mature Product)



Figures 26 and 27

Fig. 26: Surf Increases Price Variability from .420 to .600
(Static / New Product)

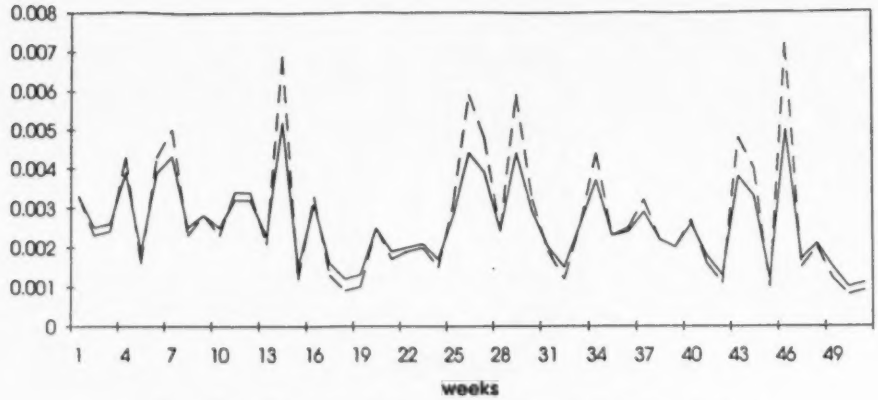
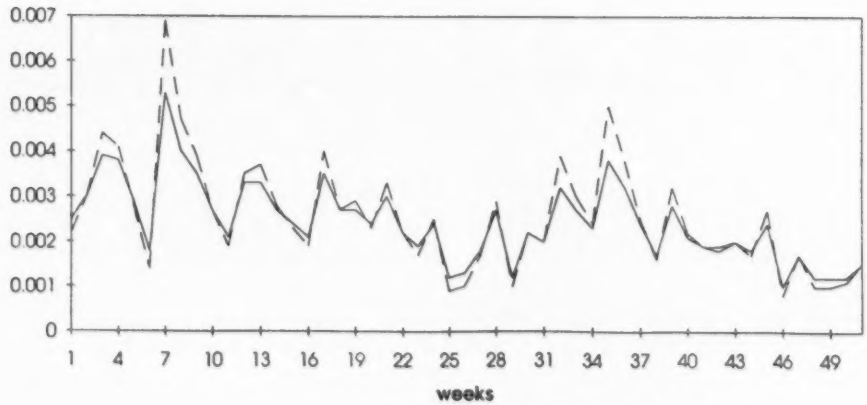


Fig. 27: Surf Increses Price Variability from .420 to .600
(Dynamic / New Product)



Figures 28 and 29

Fig. 28: Surf Increases Price Variability from .420 to .600
(Static / Mature Product)

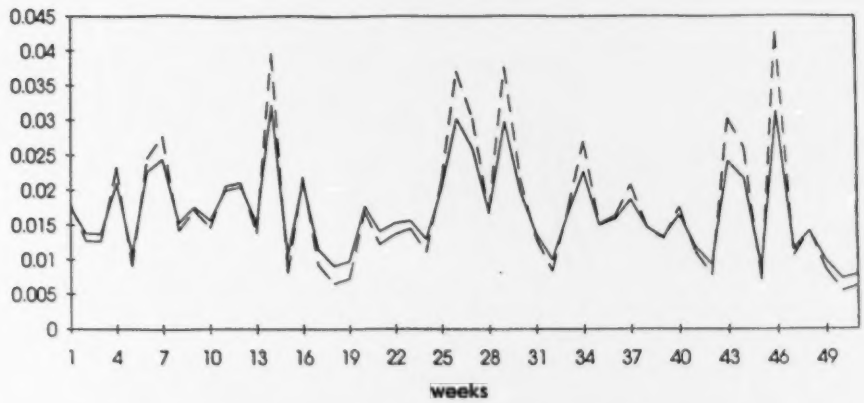
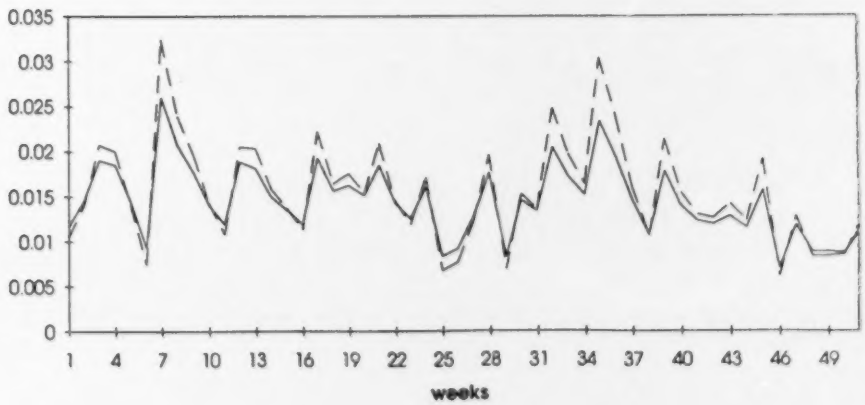


Fig. 29: Surf Increases Price Variability from .420 to .600
(Dynamic / Mature Product)



Figures 30 and 31

Fig. 30: Surf reduces Mean Price from 3.492 to 2.992
(Static / New Product)

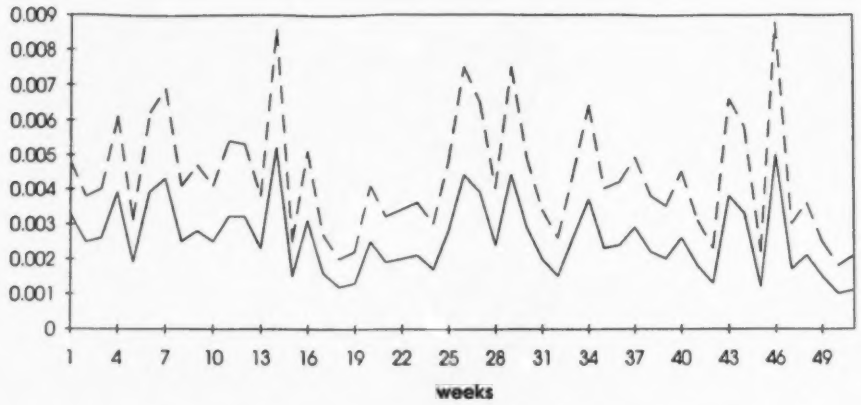
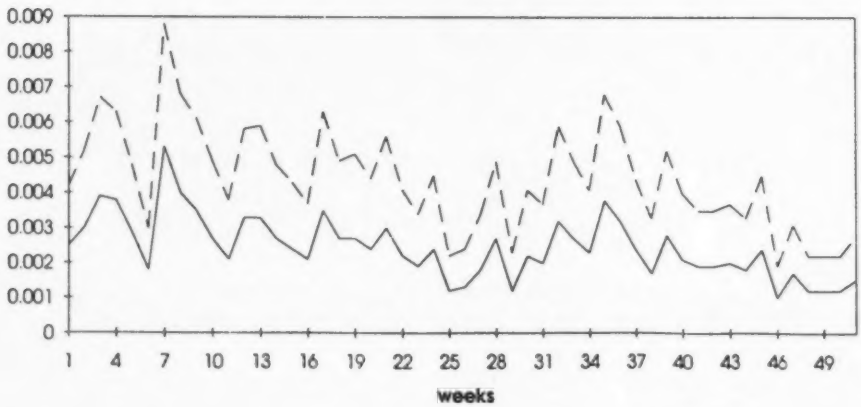


Fig. 31: Surf reduces Mean Price from 3.492 to 2.992
(Dynamic / New Product)



Figures 32 and 33

Fig. 32: Surf reduces Mean Price from 3.492 to 2.992
(Static / Mature Product)

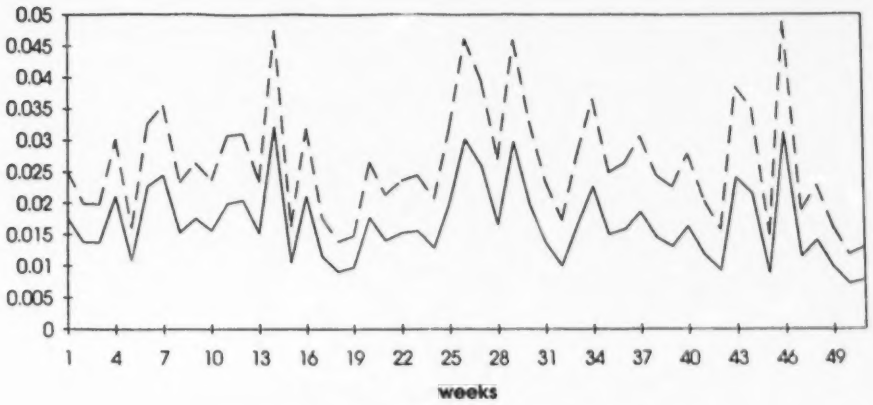
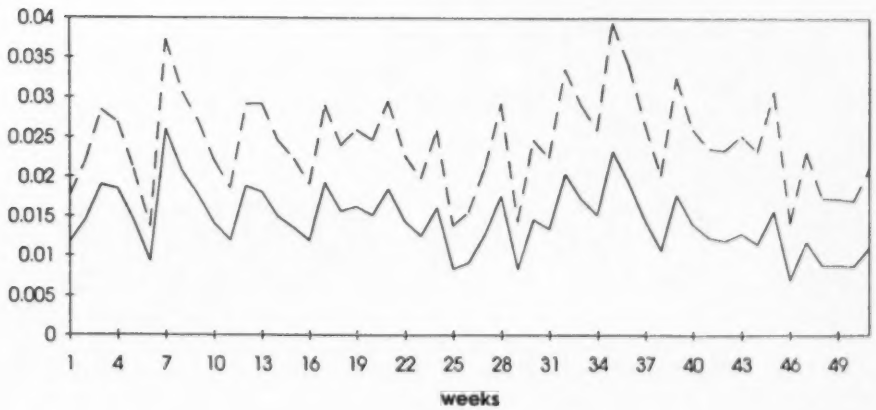


Fig. 33: Surf reduces Mean Price from 3.492 to 2.992
(Dynamic / Mature Product)



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APPENDIX 1

Extensions to the Model

My model can be extended to incorporate (1) mean attribute levels that are not constant over time, and (2) consumer search. In this section, I very briefly discuss how these extensions can be developed.

Mean attribute levels may change over time according to

$$A_{ijt} = a + A_{ij,t-1} + \rho_{ij} \qquad \rho_{ij} \sim N(0, \sigma^2_{\rho ij}) \qquad (A1.1)$$

If the mean levels of certain attributes follow a trend known to consumers, this change in attribute levels will not affect risk perceptions. Thus, a constant (a) parameter captures the "known" component of the changes in mean attribute levels over time.

Furthermore, I also posit that consumers may gather information about attribute levels via search. The information obtained via search is treated in the same way as advertising signals and information via experience. Hence,

$$R_{iijt} = A_{ij} + \kappa_{iijt} \qquad \kappa_{iijt} \sim N(0, \sigma^2_{\kappa ij}) \qquad (A1.2)$$

where R represents information obtained via search. R enters equations 16 and 17 in the same way as advertising signals and experience.

Hence the updating formula for perceived risk after the inclusion of search and non-constant mean attribute levels is

$$\sigma^2_{v\hat{i}\hat{k}jt} = \frac{1}{\frac{1}{\sigma^2_{v\hat{i}\hat{k}j,t-1} + \sigma^2_{\rho kj}} + \frac{D_{1ijt}}{\sigma^2_{\delta kj}} + \frac{D_{2ijt}}{\sigma^2_{ckj}} + \frac{D_{3ijt}}{\sigma^2_{\varepsilon kj}}} \qquad (A1.3)$$

To incorporate search in the model, consumer utility maximization is modelled as a sequential process. First, a consumer decides in each period whether to search or not (d_{irt}) which equals 1 if brand r is searched at time t and is zero otherwise. Consumer search set (R_O) is described by:

$$r \in (0,....,m) - R_0$$

Then, a consumer decides which brand to choose and as before the brand choice variable is d_{ijt} which equals one if brand j is chosen at time t and is zero otherwise. Consumer choice set is described by:

$$j \in (0,...,m) - J$$

where R_0...indexes the set of search alternatives

J....indexes the set of brands (choice set)

r....indexes search alternative

j....indexes brand

Thus, both no search and no brand choice are viable options for a consumer.

The consumer decides whether to search or not in subperiod t_I, and chooses a brand (or none) in t_{II}. The subscripts (I) and (II) of t refer to the sequential character of the consumer's problem and represent earlier and later subperiods of t.

Search influences utility by changing the information set of the consumer, which is captured by the value function (V), and imposes a cost to consumers (search costs). Thus, a term that captures search costs should be added to the utility function because I assume that utility decreases in search costs.

The impact of search as an information source is captured by the value functions. Value functions for brand choice are conditional on search choice. Thus, at time t_2,

$$V_{s(j)r}(I_{t_{II}}) = E[U_{ijrt}|I_{t_{II}}] + \gamma E[V_{s(j')r}(I_{t_{II}+1})|d_{ijrt_{II}}=1, I_{t,t_{II}}] \quad (A1.4)$$

where the information available in the second subperiod of each period depends on the search decisions made at the first subperiod.

The form of the value function in A1.4 replaces the value function in equation 21, and again results in a heterogeneous logit formula that incorporates search choice. Non-constant mean attribute levels enter the logit formula via the new updating formula for perceived risk (A1.3).

APPENDIX 2

The Seller Side of the Market: Firm's Optimal Marketing Mix and Profit Maximization

The formal model presented above focuses on the consumer side of the market by taking firms' actions to be exogenous. Firms' actions can be formalized given consumers' expected utility maximization.

The firm's profit maximization and the consumer's utility maximization problem cannot be solved together dynamically for reasons of intractability. However, the firm's problem can be introduced in a static framework to show the formal relationship between consumers and firms, and partly capture the true spirit of the conceptual framework discussed in Section III.

I posit a firm maximizing its profits for the current time period[44]. The firm's maximization problem can be expressed as follows:

$$\max_{P,AD} \Pi_{jt} = p_{jt}x_{jt}(\tilde{p}_t, \tilde{B}_t, A_{jt}, O_{jt}) - C(x_{jt}, A_{jt}, O_{jt}) - F(AD_t)$$

where j refers to a brand (and a firm because I assume that each firm produces a single brand), and t refers to time period. I use the following notation in the discussion that follows:

Π = Profits

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[44]This model has sellers maximizing only current profits. This myopic behavior is equivalent to maximizing the present value of the stream of future profits, since the model describes only stationary states.

p = Price

$\tilde{p}$ = Price vector (prices of competitors)

x = Quantity sold

$\tilde{B}$ = Vector of brand name values

A = imperfectly observable attributes

O = non-price observable attributes

C = Variable costs

F = Fixed costs

AD = Advertising

M = Market Share

P = Choice Probability as derived in Section IV

Q = Industry demand (assumed to be constant)

and again i refers to consumers (i=1,...,n) and j refers to brands (j=1,...,m).

The quantity sold is equal to the quantity demanded and is determined by the choice probabilities of consumers in the market.

$$M_j = \frac{\sum_{i=1}^{n} P_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij}} = \frac{1}{n}\sum_{i=1}^{n} P_{ij}$$

$$x_j = M_j Q$$

Brand name value (B) at time t is assumed to be a function of brand value in the previous period, advertising effectiveness and inconsistency in product positioning

$$B_{jt}=f(B_{j,t-1},h[AD_{jt},B_{j,t-1}],IC_{j,t-1})$$

Advertising effectiveness (h) is a function of advertising expenditures (AD) at time t and brand name value at t-1. Brand name value may increase the effectiveness of advertising because it increases the credibility of advertising claims.

Brand value (B) underlies the additional utility of brand names which is associated with lower perceived risk (and reduced search costs). The brand name value as perceived by a consumer is determined by the firm's actions. In turn, a firm may adjust its marketing mix according to consumer information acquisition behavior (e.g. focus on current advertising if that is all that matters to consumers).

The first-order conditions derived from the static solution to the firm's maximization problem yield straightforward implications such as brand name values increase the deviation of price from marginal cost (i.e. brand name values enable premium pricing). I do not pursue these results, but introduce the firm's problem in this section solely to show how the two sides of the market are integrated as suggested by my conceptual framework.

APPENDIX 3

A.3.1. The Dynamic Programming Problem

A consumer's expected utility maximization problem over the time span {t to T} is:

$$\max_{\{d_{ijt}\}_{t=0}^{T}} E\left(\sum_{\tau=t}^{T} \gamma^{\tau-t} U_{i\tau} | I_{it}\right) \quad 0 \le \gamma \le 1 \qquad (A3.1)$$

where γ is a discount factor. A3.1 suggests that maximization of expected utility over time is accomplished by the choice of an optimal sequence of control variables d_{ijt} for t = 0,.....,T. The dynamic programming framework converts this time series problem into a series of single period problems by introducing the concept of "value function": The value function V depends only on the information set at time t and follows the dynamic programming equation:

$$V_t(I_{it}) = E \max_{j \in J} V_{t(j)}(I_{it}) \qquad (A3.2)$$

Given this, the value function of choosing j at t is:

$$V_{t(j)}(I_{it}) = E[U_{ijt} | I_{it}] + \gamma E[V_t(I_{i,t+1}) | d_{ijt} = 1, I_{it}] \qquad (A3.3)$$

Equation A3.3 is the Bellman equation (Whitle 1982) at time t. The term after the discount factor represents the expected value function at t+1 if brand j was chosen at t. The dynamics of the problem are due to the dependence of the function V at time t+1 on the choice of d_{ijt} at time t and possibly before. The choice probability at time t can be

obtained by replacing T-1 with t, and T with t+1 in equation 26 (Chapter III).